Strategic Alliances, Venture Capital, and their Roles before IPOs and M&As

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

Faculty of Business, Economics and Social Sciences

University of Hohenheim

Institute of Financial Management

submitted by
Leonhard Brinster

from Rudnyj
2020

Date of disputation: December 9, 2020

Faculty Dean: Prof. Dr. Karsten Hadwich
Supervisor: Prof. Dr. Tereza Tykvová
Second Reviewer: Prof. Dr. Hans-Peter Burghof

Summary

The research objects of this dissertation are strategic alliances, venture capital (VC), and their roles before initial public offerings (IPOs) and mergers and acquisitions (M&As) of biotechnology and pharmaceutical companies.

Chapter 1 begins this dissertation with a general introduction and the motivation behind the research questions. Young and small businesses face several risks and difficulties, such as lack of access to finance. Highly innovative companies, therefore, often rely on VC finance. Firms offering VC provide not only financial capital, monitoring, and coaching, but also other useful resources and might encourage their portfolio companies to join strategic alliances. Such alliances can be beneficial for the portfolio companies because they provide new knowledge, access to scarce resources, or other synergies. In addition, engagement in one or many strategic alliances can have a positive signaling effect on outsiders, and thus, increase the probabilities of a successful exit (IPO or M&A).

In Chapter 2, I analyze the role of connected VC firms in strategic alliances. This chapter is co-authored with Tereza Tykvová. A reviewed version of this chapter is published in the Journal of Corporate Finance.

We study a new channel through which portfolio companies benefit from ties among venture capitalists. By tracing individual VC firms' investment and syndication histories, we show that VC firms' ties improve companies' access to strategic alliance partners. While existing studies demonstrate that alliances are more frequent among companies sharing the same VC firm, we provide evidence that alliances are also more prevalent among companies indirectly connected through VC syndication networks. In addition, our results suggest that VC firms' ties mitigate asymmetric information problems that arise when alliances are formed. Finally, we demonstrate that this type of alliance is associated with higher IPO

probabilities. We also provide alternative explanations of alliance formation and address related endogeneity concerns.

The research objective of the third chapter is to determine the role of strategic alliances in VC exits. This chapter is co-authored with Christian Hopp and Tereza Tykvová. A reviewed version of this chapter is published in Venture Capital.

Chapter 3 contributes to a better understanding of the relationship between strategic alliances and VC exits. The recent empirical literature concludes that alliances improve the probability of successful exits for venture-backed companies. When we control for observed and unobserved heterogeneity in a cohort sample of companies, self-selection into alliance activity, and censoring, we find the effect to be smaller than evidenced in prior studies. Moreover, we confirm the positive effect of alliances only for IPOs and not M&As. These findings are consistent with the view that strategic alliances help companies certify their quality for potential buyers.

Chapter 4 investigates the role of strategic alliances before M&As in more detail. This chapter is a single-authored manuscript by Leonhard Brinster.

Based on a large sample of M&A deals, I estimate the role of different types of ties between companies. I distinguish related alliances into direct and indirect alliances. Related alliances provide access to more information and can reduce transaction costs by reducing the time from announcement to completion of the M&A deal. The reduction of such costs can lead to a more successful target selection and increase the transaction process efficiency of the M&A deal. This effect can be explained by trust-building, better access to private information, and certification through related alliances. The empirical results show a positive relationship between related alliances and the likelihood of an M&A. However, in contrast to other studies, I do not find statistically significant evidence that supports the hypothesis that alliances increase the post-M&A performance and that alliances are associated with higher announcement returns.

Finally, Chapter 5 concludes the dissertation with a short summary of the main findings and an outlook for future research.

Zusammenfassung

Der Forschungsgegenstand dieser Dissertation sind strategische Allianzen, Risikokapital (VC) und ihre Funktionen vor Börsengängen (IPOs) und Fusionen & Übernahmen (M&As) von Biotechnologie- und Pharmaunternehmen.

Kapitel 1 dieser Dissertation beginnt mit einer allgemeinen Einführung und der Motivation hinter den Forschungsfragen. Junge Unternehmen stehen am Beginn ihrer Geschäftstätigkeiten vor diversen Risiken und Schwierigkeiten. Insbesondere innovative Firmen greifen auf Risikokapital zurück. Allerdings bieten VC-Investoren nicht nur Finanzkapital, Kontrolle und Coaching, sondern auch andere nützliche Ressourcen. VC-Investoren könnten zudem auch andere ihrer Portfoliounternehmen dazu animieren, strategische Partnerschaften einzugehen. Solche Allianzen können für die Unternehmen vorteilhaft sein und Synergien führen, denn sie liefern Zugang zu neuem Wissen und knappen Ressourcen. Zusätzlich kann eine strategische Allianz ein positives Signal für Außenstehende sein und die Wahrscheinlichkeit eines erfolgreichen Ausstiegs (IPO oder M&A) erhöhen.

In Kapitel 2 analysiere ich die Wirkung von verbundenen VC-Firmen in strategischen Allianzen. Kapitel 2 wurde gemeinsam mit Tereza Tykvová verfasst und eine überarbeitete Version wurde im Journal of Corporate Finance veröffentlicht.

Wir untersuchen einen neuen Weg, durch den Portfoliounternehmen aufgrund der Beziehungen zwischen den Risikokapitalgebern profitieren. Durch Nachverfolgung der Investitionshistorie einzelner VCs zeigen wir, dass die Beziehungen der VCs den Zugang der Unternehmen zu strategischen Allianzpartnern verbessern. Während andere Studien zeigen, dass Allianzen häufiger zwischen Unternehmen mit gleichen VC-Investoren zu finden sind, liefern wir den Beweis, dass Allianzen auch häufiger bei Unternehmen anzutreffen sind, die indirekt durch VC-Syndizierungs-Netzwerke verbunden sind. Darüber hinaus legen unsere Ergebnisse

nahe, dass durch Beziehungen der VC-Investoren Informationsprobleme, die bei der Bildung von Allianzen auftreten, abschwächen. Schließlich zeigen wir, dass diese Art von Allianz mit höheren IPO-Chancen verbunden ist. Wir befassen uns zudem auch mit alternativen Erklärungen der Bildung strategischer Allianzen und damit verbundenen Endogenitätsproblemen.

Das Forschungsziel in Kapitel 3 ist die Bestimmung der Rolle der strategischen Allianzen bei VC-Ausstiegen. Dieses Kapitel wurde gemeinsam mit Christian Hopp und Tereza Tykvová verfasst. Eine überarbeitete Version dieses Kapitels wurde in Venture Capital veröffentlicht.

Aktuelle empirische Literatur kommt zu dem Schluss, dass Allianzen die Wahrscheinlichkeit erfolgreicher Ausstiege für VC-finanzierte Unternehmen erhöhen. Wenn wir aber die Schätzungen auf Heterogenität der Unternehmen, die Selbstselektion in Allianzaktivitäten und auf zensierte Daten kontrollieren, finden wir einen kleineren Effekt, als in früheren Studien. Außerdem bestätigen wir die positive Wirkung von Allianzen nur bei IPOs, nicht aber bei M&As. Diese Feststellungen stehen im Einklang mit der Ansicht, dass Allianzen Unternehmen helfen, ihre Qualität für potenzielle Käufer zu zertifizieren.

Kapitel 4 untersucht die Rolle strategischer Allianzen vor M&As im Detail. Dieses Kapitel ist ein von Leonhard Brinster verfasstes Manuskript.

In diesem Kapitel nehme ich eine Einschätzung der Funktion verschiedener Typen früherer Beziehungen zwischen den Unternehmen vor. Bei verbundenen Allianzen unterscheide ich zwischen direkten und indirekten Allianzen. Diese Allianzen bieten zusätzliche Informationen und können die Transaktionskosten senken. Die Reduzierung solcher Kosten kann zu einer erfolgreicheren Auswahl eines Zielunternehmens und zu einem effizienteren Transaktionsprozess führen. Grund hierfür ist die Zeitersparnis von der Ankündigung bis zum Abschluss des M&A-Geschäfts. Dieser Effekt lässt sich durch Vertrauensbildung, besseren Zugang zu privaten Informationen und Zertifizierung durch verbundene Allianzen erklären. Allerdings finde ich keine statistisch signifikanten Beweise für die Hypothese, dass Allianzen die Leistungsfähigkeit nach M&As erhöhen und dass Allianzen mit höheren Ankündigungsrenditen verbunden sind.

Das Kapitel 5 schließt die Dissertation mit einer kurzen Zusammenfassung der wichtigsten Ergebnisse und einem Ausblick für zukünftige Forschungsgebiete ab.

Contents

List of Figures

List of Tables

Chapter 1

General Introduction

Young companies face several risks and difficulties during their nascent phase. Due to the lack of experience, tangible assets, business contacts, and a successful track record, young entrepreneurial companies face enormous challenges in access to finance and other vital resources. Although commercial bank loans are a major finance source for small businesses[1], highly innovative companies prefer VC finance and their expertise. This behavior applies especially for companies that have a risky strategy and uncertain future profitability (Winton and Yerramilli 2008). Often in exchange for stakes of ownership, VC firms provide financial capital for companies to grow and expand their business. However, VC firms offer not only financial capital but also other useful resources (Cumming et al. 2005; Gompers and Lerner 2000; 2004; Sahlman 1990). They monitor their portfolio companies more frequently (Gorman and Sahlman 1989) than banks and ensure that entrepreneurs stay on "track" and do not waste their resources. Moreover, VC firms often join the board of directors of invested companies, thereby providing knowledge and expertise for young and inexperienced entrepreneurs (Fried et al. 1998).

In recent years, academics have studied new channels through which VC firms help improve their portfolio companies (see, e.g., Lindsey 2008). Strategic alliances are relationships between two or more companies to pursue a common objective through mutual cooperation or pooling of resources. VC firms encourage their portfolio companies to join strategic alliances. Such alliances can be beneficial

[1]See, e.g., Berger and Udell (1998) for a survey of small businesses in the United States.

for portfolio companies because of their knowledge, access to scarce resources, or other synergies. In addition, engagements in strategic alliances can have a positive effect on outsiders because, for instance, another company was willing to enter an alliance with that company. This can be a certification of good quality and promising business of the portfolio companies.

The certification effect can also be beneficial for VC firms, as their objective is high returns for their investments. Therefore, they pursue two main channels to achieve their objective: either go for an IPO or aim at a trade sale, for example, an M&A of their portfolio companies.

Figure 1.1 illustrates the context between alliances, VC, and exits.

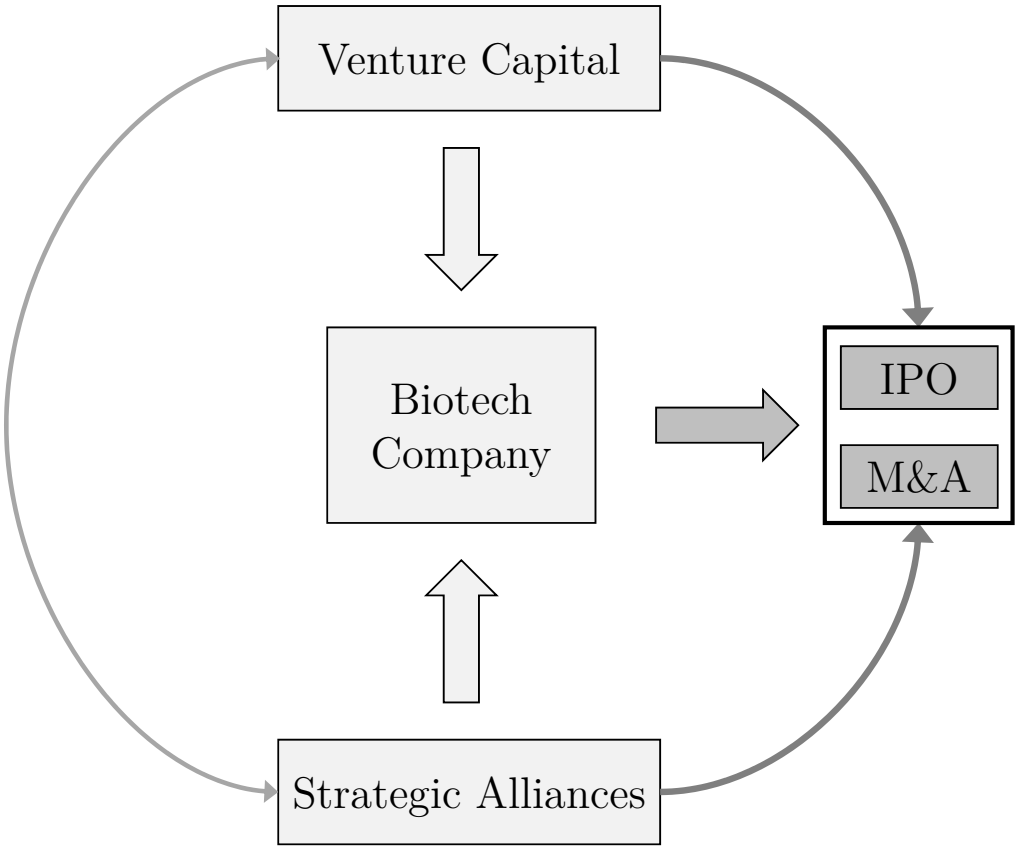

Figure 1.1. The relationship between strategic alliances, VC, and exits

On the one hand, the biotechnology company requires financial capital, and

thus, seeks investments from VC firms. On the other hand, VC firms might see the beneficial effects of strategic alliances, and hence, encourage their portfolio companies to engage in such partnerships, which can ultimately lead to a successful exit. This is the main goal for both parties in the future.

The effect of strategic alliances on VC exits, that is, IPO or M&A, are subjects of recent studies (see, e.g., Lindsey 2008; Ozmel et al. 2013b; Wang et al. 2012). However, the subject of strategic alliances in the context of VC, IPOs, and M&As is not thoroughly researched and some questions remain unanswered in the empirical finance literature. For example, Lindsey (2008) finds that companies from the same VC portfolio are more likely to enter strategic alliances. However, there is no clear evidence of the role of prior ties of VC firms and how they affect the choice of alliances.

Other studies find that strategic alliances increase the likelihood of being acquired or going public (Lindsey 2008; Ozmel et al. 2013b; Qi et al. 2015; Wang et al. 2012). The role of strategic alliances and different types of prior ties before M&As is not fully understood as the results in the current literature are mixed. In addition, previous ties of VC firms and those between the acquirer and the target might play a critical part in the likelihood of going public or being acquired.

Moreover, concerns about endogeneity issues remain unexplained, and questions about the validity of the results remain partly unanswered. Possible other explanations for the proposed effects must be explored, and more empirical evidence is necessary. This dissertation fills some remaining gaps in the extant literature on strategic alliances and VC.

The final goal of this dissertation is to shed more light on the relationship between strategic alliances and VC. I gratefully acknowledge access to S&P Capital IQ, Dow Jones VentureSource, Thomson VentureXpert, Thomson SDC, and Patstat, provided by DALAHO, University of Hohenheim. Further, this dissertation aims to identify new channels and causal links between alliances, IPOs, and M&As. The three underlying studies of this dissertation are aimed at identifying endogeneity issues, possible solutions, and potential explanations for the results of the empirical analyses.

Figure 1.2 shows the structure of this dissertation.

After the introduction in the first chapter, the research continues to cover the

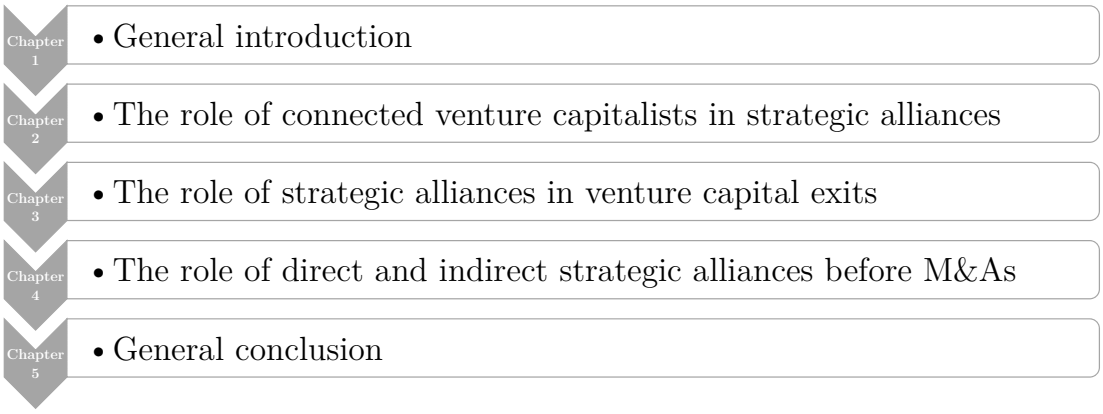

Figure 1.2. Structure of the dissertation

role of connected VC firms and strategic alliances in the second chapter. The main question that is addressed in this study is whether two companies ally more often if they are backed by connected VC firms, that is, firms that invested in the same company in the past. I investigate whether the portfolio companies of connected VC firms are more likely to ally. There are three reasons why this should be the case. First, VC firms that are connected might mitigate the transaction costs of alliance formation by helping their portfolio companies to establish contacts with portfolio companies from the connected VC portfolio. Second, a connected VC firm can reduce adverse selection costs. Third, because of reputational reasons, connected VC firms may protect the counterparty from moral hazard and expropriation risks by limiting misconduct in their portfolio companies. The empirical analyses show that alliances are more frequent among companies indirectly connected through VC syndication networks. In addition, the results suggest that companies with strategic alliances from connected VC firms are more likely to have an IPO.

After the results from the second chapter and the findings that prior connections between VC firms are relevant for the creation of strategic alliances, the third chapter presents the role of strategic alliances in VC exits. Exits in the form of IPOs or M&As are favorable exit options for investors. Although IPOs deliver the highest return on investment, M&As are more common (Cumming and MacIntosh 2003). However, due to the absence of sufficient collateral, the information avail-

able on the quality of a project or company differs between the seller and the buyer. Therefore, a successful exit is uncertain. Certification through a third party is one way to mitigate the information asymmetry between contracting parties. This chapter attempts to answer whether strategic alliances may serve as a certifying device and whether their role differs based on the type of exit. After controlling for observed and unobserved heterogeneity, and other endogeneity issues, the effect is smaller than those evidenced in prior studies. Moreover, the analysis shows a positive effect of alliances only for IPOs and not M&As.

Finally, the results of the previous chapter lead to the fourth chapter. Because the effect of alliances on M&As is ambiguous, in this chapter, I examine the role of different alliances before M&As. I categorize alliances into related and unrelated strategic alliances. Related alliances are further distinguished into direct and indirect alliances. M&A deals, where the acquirer and target company have a strategic alliance before the deal, are considered to have a direct tie. Cases where the acquirer and target company have ties through other alliances, that is, both companies share a common strategic partner, are considered to have an indirect tie. Related alliances can provide access to more information and potentially reduce transaction costs. Therefore, such prior ties can be beneficial in the target selection and deal transaction process. Because of trust-building, better access to private information, and certification through prior ties, the probabilities of a successful M&A deal increase.

The final chapter concludes this dissertation with a summary of the key facts and a brief outlook for potential future research.

Chapter 2

Connected VCs and Strategic Alliances[1]

Abstract

We study a new channel through which portfolio companies benefit from ties among venture capitalists (VCs). By tracing individual VCs' investment and syndication histories, we show that VCs' ties improve companies' access to strategic alliance partners. While existing studies demonstrate that alliances are more frequent among companies sharing the same VC, we provide evidence that alliances are also more frequent among companies indirectly connected through VC syndication networks. In addition, our results suggest that VCs' ties mitigate asymmetric information problems that arise when alliances are formed. Finally, strategic alliances between companies from connected VCs' portfolios tend to perform well. We demonstrate that this type of alliance is associated with higher IPO chances. We also address alternative explanations and related endogeneity concerns.

JEL *classification:* G24, L24, L26

[1]This is an Author's Original Manuscript of an article published by Elsevier in the Journal of Corporate Finance available online at `https://doi.org/10.1016/j.jcorpfin.2020.101835`. Earlier versions of this chapter were presented at the 22nd Annual Interdisciplinary Conference on Entrepreneurship, Innovation and SMEs; 3rd Entrepreneurial Finance Conference; European Financial Management Association 2019 Annual Meetings; 26th Annual Meeting of the German Finance Association; and Financial Management Association 2019 Annual Meetings.

2.1 Introduction

Venture capitalists (VCs) are financial intermediaries that offer funds to high-growth companies. Besides funds, they add value to these companies by providing coaching and mentoring. In addition, they facilitate high-growth companies' access to "third parties" such as further investors, human capital, suppliers, customers, public institutions, industry associations, and strategic alliance partners (e.g., Sahlman 1990). In this study, we focus on VCs' role in the formation of strategic alliances. Strategic alliances are an important source of value for young innovative companies because they link them to other companies with complementary resources (Mitchell and Singh 1996; Pisano 1994; Shan et al. 1994; Singh and Mitchell 2005; Stuart 2000). These links may improve companies' prospects, and help them grow and reach their goals (e.g., Ozmel et al. 2013a).

Prior research suggests that VCs increase the alliance activity in their portfolio companies (e.g., Ozmel et al. 2013b). From the existing literature, we also know that two VC-backed companies that obtained funding from the same VC form alliances more often than those that were financed by two different VCs do (Lindsey 2008). This paper investigates whether portfolio companies benefit from bilateral ties among VCs when they form strategic alliances.

We ask the question whether two companies more often form an alliance if they were backed by VCs that are connected with each other. We expect to find a positive answer for at least three reasons. First, two VCs that are connected may mitigate the transaction costs of alliance formation by helping their portfolio companies to establish contacts with portfolio companies from the connected VC portfolio. Second, a connected VC can reduce adverse selection costs. Since a connected VC enjoys a higher level of trust than an unknown VC does, it may certify its portfolio company quality for the partner company. Third, for reputational reasons, connected VCs may protect the counterparty from moral hazard and expropriation risks by limiting misconduct in their portfolio companies.

To illustrate what we mean by connected VCs, Figure 2.1 shows, on the right-hand side, an example of a connected-VC-backed alliance between company X (backed by VC_1) and company Y (backed by VC_2). VC_1 and VC_2 are "connected" because they invested jointly in company Z in the past. For comparison purposes,

we show a same-VC-backed alliance on the left-band side. Companies A and B, which were both backed by VC_1, pair in an alliance.

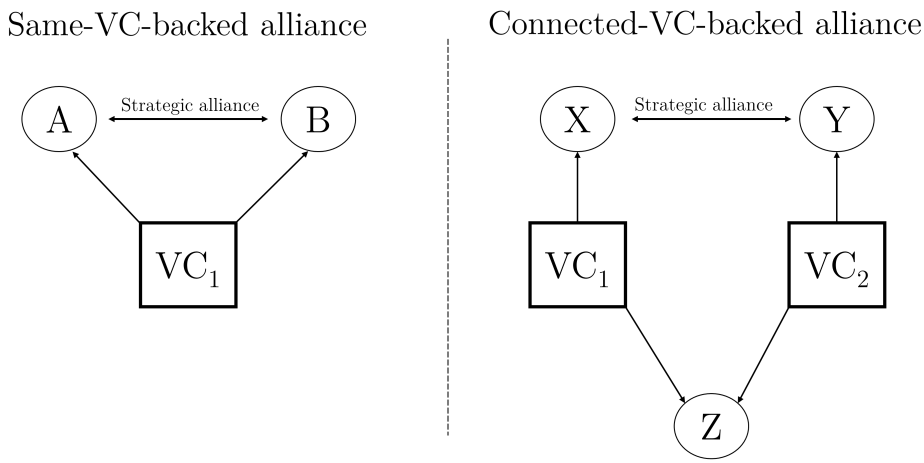

Figure 2.1. Same-VC-backed and connected-VC-backed strategic alliances

We also investigate whether bilateral connections between VCs are more important when transaction and information costs increase; that is, when the geographical and technological distances between the potential alliance partners grow. Finally, we are interested whether alliances between companies from connected VCs' portfolios are associated with better exits.

To answer these questions, we rely on a dataset of 683 strategic alliances formed between 2004 and 2016 by 202 VC-backed US biotech companies. In 295 cases (43.2%), both the biotech company and the alliance partner are VC-backed. In 51 of these cases, both alliance partners share the same VC. Alliances between companies from connected VCs' portfolios are even more common: we observe 188 such alliances in our sample.

Our results suggest that bilateral ties between VCs tend to improve companies' access to strategic alliance partners from connected VCs' portfolios. We address alternative non-causal explanations for the positive link between bilateral VC connections and alliance activity between companies from connected VCs' portfolios. We are aware that VCs with large networks invested with many different VCs in the past. Thus, the probability that a connected VC will participate in the alliance with a particular partner is, in general, higher for VCs with large networks

than for VCs with small networks (Ozmel et al. 2013b). To illustrate, imagine a very large VC that already invested with all other VCs in the past. Consequently, this VC will have ties to all VCs in all VC-backed partners. Consequently, the effect we observe could be the overall-network-effect instead of the bilateral-ties-effect. Therefore, in our analyses, we disentangle these two effects and measure the bilateral-ties-effect on the top of the overall-network-effect.

Another alternative explanation for the positive relationship between bilateral ties and alliances could arise from VC specialization. Two VCs with the same industry focus are more likely to be connected through prior joint investments. At the same time, companies from the same industry could more likely form an alliance than companies from different industries would. Consequently, we might observe strategic alliances between companies financed by connected VCs more often because these VCs have a similar investment focus. We indeed find that strategic alliances between the portfolio companies of VCs with a similar investment focus are more likely to occur. However, the effect of bilateral ties remains highly statistically significant and positive when we control for the similarity of the investment focus of the two VCs.

We also account for a non-random matching between alliance partners. We want to link the probability that biotech company X and strategic partner Y form an alliance to proxies that capture how closely the VCs of X and Y are connected (if they are connected). To analyze this probability, we build a sample of counterfactual alliances; that is, alliances that were possible but that did not occur. We employ two different ways to construct the sample of counterfactual alliances. In the first approach, for each realized alliance of each biotech company, we define alternative alliance partners as those companies that formed another strategic alliance around the same time. The second approach chooses those companies as alternative partners that have similar characterstics as the chosen partner.

This research contributes to four main strands of the literature. First, we provide new findings on the relationship between VC financing and strategic alliance activity. This topic attracted attention since the seminal study by Lindsey (2008), who finds that strategic alliances are more common among companies financed by the same VC. While she considers positive effects of VC financing on alliance formation only within a particular VC's existing and prior portfolios, we expect

to find a positive effect also between the portfolios of connected VCs. Another related study is that by Wang et al. (2012), who show that larger VC syndicates are associated with a higher number of strategic alliances on average. While they only look at the relationship between the overall VC network and the alliance activity, we delve into the effects of individual prior ties within VC syndicates on the choice of a particular strategic partner. More specifically, we extend the existing knowledge by analyzing how prior ties between two VCs affect the cooperation patterns of companies backed by these VCs. We expect that VC-backed companies are more likely to engage in strategic alliances with companies in which a connected VC invested. Hereby, connected VCs may reduce transaction costs for the partners' portfolio companies. In addition, connected VCs may mitigate the adverse selection and moral hazard costs that arise between alliance partners. Our results support this view.

We are the first to analyze whether portfolio companies benefit from their VCs' prior bilateral ties through a better access to strategic alliance partners from individual network VCs' portfolios. Ozmel et al. (2013b) mention that prominent VC networks may help portfolio companies find appropriate alliance partners. They show that larger VC network size is positively associated with alliance formation. However, they do not collect data on individual VCs' financing histories. Our study builds on Ozmel et al. (2013b)'s findings. However, instead of relying on the overall VC network size only, we offer a direct evidence by tracing specific VC ties. We look at the individual VC financing histories of both alliance partners and trace the prior joint bilateral ties between VCs participating on both sides of the alliance. We then analyze whether these ties (and their intensity) matter for alliance pairing. We demonstrate that, while controlling for the overall network size, bilateral VC ties help companies build alliances with partners from connected VCs' portfolios. In addition, these ties matter more when transaction and information costs increase.

Second, we add to the literature that focuses on the effects of VC syndication and networks. Recent theoretical and empirical work studies the involvement of several VCs as a common means to access new financial and managerial resources. The findings suggest that VCs and portfolio companies benefit from cooperation among VCs. In essence, cooperation among VCs affects the main drivers of perfor-

mance: sourcing high-quality deals, and promoting growth and innovations in the portfolio companies. The benefit of involving co-investors comes from the heterogeneous skills and information sets that different VCs contribute to the selection and management of the portfolio companies. Lerner (1994) suggests that the evaluation of the same venture proposal by different VCs operating in a syndicate reduces adverse selection. From existing research we know that VCs share access to deals with connected VCs (Tian 2012). We find that VCs may share access to potential cooperation partners from their portfolios in a similar way. Brander et al. (2002) see the VC industry as a pool of productive resources in which a VC can access resources from another VC through joint investments. Other studies demonstrate that cooperation among VCs yields higher sales or employment growth (e.g., Grilli and Murtinu 2014; Tian 2012) and more innovations (e.g., Bertoni and Tykvová 2015). Hochberg et al. (2007) analyze the performance consequences of the ties formed in the US venture capital industry and show that portfolio companies whose investors are better connected perform substantially better. We contribute to this research by showing how prior ties among VCs are related to the formation of ties between portfolio companies.

Third, we contribute to the more general literature on VC value added. Numerous studies argue that VCs add value to their portfolio companies beyond money. VCs monitor their portfolio companies, which reduces agency costs (Gompers 1995; Lerner 1995). In addition, their companies benefit from VCs' support in important strategic decisions and activities (see, e.g., Cumming et al. 2005; Hellmann and Puri 2002; Hochberg et al. 2007; Hochberg 2012; Kaplan and Strömberg 2004). While many studies demonstrate value creation in VC-backed companies[2], though only a few studies focus on a specific area of involvement through which VCs add value. Our study contributes to filling this gap by shedding light on one of these areas, namely, strategic alliance formation. Moreover, we find that strategic alliances between portfolio companies from connected-VCs' portfolios are associated with better exits.

[2]For example, there is empirical evidence for a positive relation between venture capital financing and innovation at the country-level (e.g., Kortum and Lerner 2000; Popov and Roosenboom 2012) and portfolio company-level (e.g., Bertoni and Tykvová 2015; Hellmann and Puri 2000). Other studies show positive effects on employment or sales growth, valuations, and survival (for a survey, see Tykvová 2018).

Finally, we add to the literature in the management and strategy area that argues that indirect ties result in direct ties (Gulati 1995b), and that networks are related to alliance formation (Gulati 1998; 1999). Gulati (1995b) analyzes the social network in which a company is embedded, because such networks potentially provide valuable information about partners. Therefore, the position of a company in a social network has an impact on future alliance formation; that is, the smaller the distance between two companies is, the more likely it is that they will form an alliance. Furthermore, networks may serve as a governance mechanism for inter-company connections (e.g., Robinson and Stuart 2007b). The authors argue that "information conveyed through network ties is not necessarily available to all network members" and that in strategic alliances, companies "rely less on explicit control mechanisms such as equity ownership and more on implicit, network-based control." We show that prior connections between VCs increase the probability of alliance formation, arguably because prior connections result in a more efficient screening result, and thus in less need for explicit control mechanisms such as equity ownership. Singh (2008) reports that social networks are important predictors of intraregional and intracompany knowledge flows. Our results demonstrate that prior connections between the VC-investors can mitigate the negative effects of greater distance on alliance formation. To summarize, we complement this literature by focusing on prior ties between VCs and their effects on networking among portfolio companies in the form of alliance formation.

The remainder of the paper is structured as follows. The next section presents the theoretical background for this study. We discuss our dataset in Section 2.3, where we also provide the descriptive statistics of the VC-backed biotech companies and their strategic alliances. Section 2.4 first describes the methodology we use to construct the sample of counterfactual alliances. Next, we compare the characteristics of the realized and counterfactual alliances. Section 2.5 shows our empirical results and Section 2.6 concludes.

2.2 Theoretical background

Despite their popularity and the acclaimed benefits (e.g., Chan et al. 1997), many strategic alliances fail to meet expectations. For example, Das and Teng (2000)

report that 30 to 50% of strategic alliances do not succeed. Reuer et al. (2002) report that 34% of research alliances are failures and Sadowski and Duysters (2008) claim that more than 50% of technology alliances do not survive.

At first, it is costly to find an appropriate partner and the selection process suffers from information asymmetries since the potential partner's quality is unknown to the other party (Owen and Yawson 2013). Strategic alliances appear fragile for several reasons. After the two parties form an alliance, each may be exposed to moral hazard. The joint involvement in a business generates incentives to free ride on the information acquisition and the effort of the other party (Das and Teng 1999; 2001; Fonti et al. 2017). Additionally, close collaboration in the form of a strategic alliance may lead to information leakage to the other party, which is a strategic partner on the one hand, but also a competitor that may misuse this information (Hamel et al. 1989) on the other hand. Consequently, each company may consider expropriation risks when deciding if to collaborate and with which partner (Gulati and Singh 1998).

These problems are particularly pronounced in young biotech companies. In the first years of existence, biotech companies generally do not have enough experience to identify beneficial business combinations and appropriate collaboration partners. They typically do not enjoy large networks that they can tap to find these partners. Consequently, they usually face larger transaction and adverse selection costs than established companies or companies from traditional sectors (Baum et al. 2000; Robinson and Stuart 2007a). As young biotech companies develop new, potentially highly valuable products, they also face moral hazard and expropriation risks (Diestre and Rajagopalan 2012; Rothaermel 2001a;b; Rothaermel and Deeds 2004; Yang et al. 2014). From the view of the potential partner, the uncertainty regarding the future outcomes is substantial because young biotech companies usually do not have tangible assets but rather intangible assets.

Firms can reduce asymmetric information, moral hazard, and expropriation risks by screening and monitoring the counterparty (Kaplan and Strömberg 2001; 2004; Lerner 1995). However, the ex-ante quality and ex-post actions of the counterparty are costly to observe, so screening and monitoring will prohibitively increase the costs of alliance formation and cooperation (Dyer and Chu 2003; Gulati and Singh 1998; White and Siu-Yun Lui 2005). Under these circumstances, it

seems challenging for young biotech companies to find well-fitting and reliable strategic partners that are willing to invest.

When parties find it costly to accurately evaluate the quality of resources that partners can bring to the table, informed active investors and their certification of partners can be valuable (Hochberg et al. 2007; Hsu 2004; Megginson and Weiss 1991). In this environment, connected VCs may provide several benefits. VCs, as active investors, have access to detailed information about the companies they finance, and hence understand their portfolio companies' needs (Barry et al. 1990). This understanding may help young firms find appropriate partners (Aoki 2000). Consequently, they may launch beneficial business combinations within their own and connected VCs' existing and prior portfolios, and mitigate problems stemming from both asymmetric information and the transaction costs associated with partner search.

Because VCs interact beneficially with the same VCs repeatedly, they want to maintain their good reputation within the network of connected VCs. VCs are interested in further collaboration, and therefore avoid undesirable behavior towards other connected VCs. Otherwise, they could fear that their prior friends will withhold future beneficial cooperation. Therefore, connected VCs are a well-suited certification device (Hochberg et al. 2007; 2010). In addition, VCs want to attract promising, high-quality entrepreneurs. As high-quality entrepreneurs tend to match with high-quality VCs (Hsu 2004; Sørensen 2007), maintaining a good reputation is crucial for a high-quality deal flow. Consequently, a VC that gains a reputation as a reliable investor associated with beneficial business combinations is more likely to attract better deals and obtain a better position within its network. Portfolio companies financed by connected VCs thus enjoy more trust than companies coming from outside the network. In turn, adverse selection costs and uncertainties decrease. Additionally, connected VCs may limit misconduct in their portfolio companies. When the VCs still hold control rights in their portfolio companies, they may discipline companies' management and thus protect the counterparty from moral hazard and expropriation risks.

Consequently, we expect that prior ties among two VCs are associated with an increase in the probability that two companies from the portfolios of this VC pair will form a strategic alliance. We assume that the connected-VC-effect should be

stronger when companies face greater information and transaction costs; that is, when the geographical and technological distances between two potential alliance partners increase.

2.3 VC-backed biotech companies and their strategic alliances

We consider the strategic alliances of young VC-backed biotechnology companies. We extract information about all VC-backed biotechnology companies founded between 2004 and 2008 in the US. To obtain this information, we combine the Dow Jones VentureSource and Thomson One VentureXpert databases. We rely on a cohort of companies from one country that are of a similar age and belong to one industry. We construct this homogeneous sample in order to reduce concerns of unobserved heterogeneity that could otherwise arise due to the firms' differing development stages and country or industry characteristics.

For all companies in our sample, we extract data on their VC financing (Dow Jones VentureSource, Thomson One VentureXpert and S&P Capital IQ), patents (Patstat), company characteristics (S&P Capital IQ), and exits (Dow Jones VentureSource and Thomson One VentureXpert) until 2016. After excluding companies that did not disclose the names of their VCs, we have 738 companies. We then collect data on these companies' strategic alliance activity between 2004 and 2016 from S&P Capital IQ. S&P Capital IQ uses a narrow definition of a strategic alliance as a "relationship between two or more companies to pursue a common objective through mutual cooperation, pooling of resources, etc." (`https://www.capitaliq.com/`). This definition does not include joint ventures and other business relationships such as licensing, distribution, or franchising. According to this definition, 202 sample companies entered one or more strategic alliances. In total, we count 683 strategic alliances.

Figure 2.2 displays the geographical location of the 202 sample companies with strategic alliances. We observe clustering in a few US states, such as California, Massachusetts, and New Jersey.

Table 2.1, Panel A reports the descriptive statistics of the sample companies.

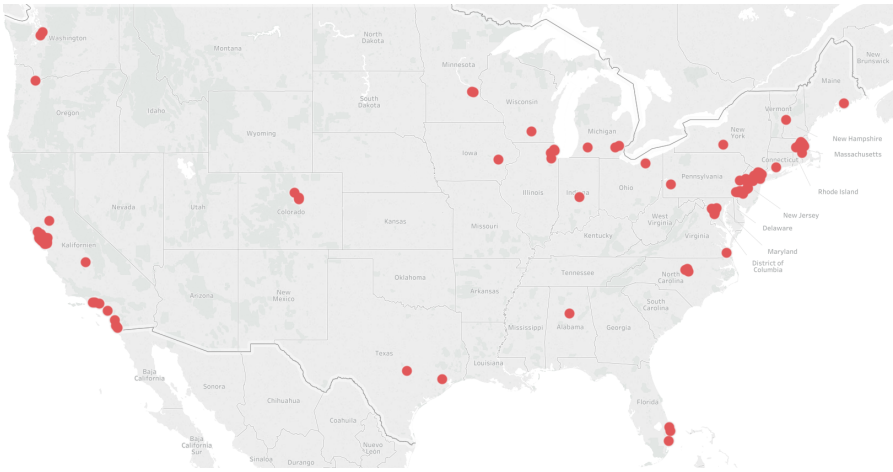

Figure 2.2. Geographical location of biotech companies

At the time of the first alliance, the biotech companies are on average 5.21 years old (median is 4.74) and the mean number of VC rounds is 2.20 (median is 2). On average, a sample company applied for 7.03 patents, with the median number of patent applications being 3, and a few companies already obtained a large number of patent applications when they enter their first strategic alliance (the maximum number is 147). Biotech companies obtained financing from 4.4 different VCs on average, 32% of them being foreign. Prior to their first investment in the biotech company, the involved VCs invested in 67 companies on average and have 255 total ties to other VCs from prior syndicated investments. Finally, 24% of the biotech companies from our sample reached an IPO exit.

Next, we turn to the strategic alliance partners of our sample companies. There are 497 unique strategic alliances partners. Figure 2.3 displays their geographical location. Approximately 35% of all partners are located outside the US, mostly in Western Europe.

For the strategic alliance partners, we extract data on their VC financing and other company characteristics. Table 2.1, Panel B shows that at the time of their first strategic alliance, 40% of the strategic alliance partners in our dataset are VC-backed, with an average number of 3.34 rounds (median is 2). Compared to the biotech companies from our sample, the VC-backed partners usually have more VCs (the median number is 5 versus 3) and a higher fraction of non-US VCs (the median is 0.44 versus 0.29). In addition, their VCs have slightly more experi-

Figure 2.3. Geographical location of strategic alliance partners

ence, but slightly weaker networks. However, these differences are not statistically significant. Strategic alliance partners are substantially older than the biotech companies are. Their median age is 24 years. Of the strategic alliance partners, 20.12% are from the biotechnology industry, 22.13%) are from the pharmaceutical industry, and the remaining 57.8% are from other industries.

2.4 Realized and counterfactual strategic alliances

2.4.1 Construction of the counterfactual alliances sample

Alongside the sample of 683 realized alliances, we build a sample of counterfactual (potential) alliances. To each realized alliance, we match six counterfactual alliances. The comparison between the sample of realized alliances and the sample of counterfactual alliances will help us in answering whether prior VC ties are beneficial for pairing companies from connected VCs' portfolios in an alliance. The counterfactual sample consists of combinations between biotech companies and strategic partners that were possible, but that never occurred.

Figure 2.4 visualizes how we build the sample of counterfactual alliances. In this figure, we depict all realized strategic alliances closed within a certain period. On the left-hand side of the figure, we have our sample biotech companies A through I that were active within this period. Company A pairs in a strategic alliance with

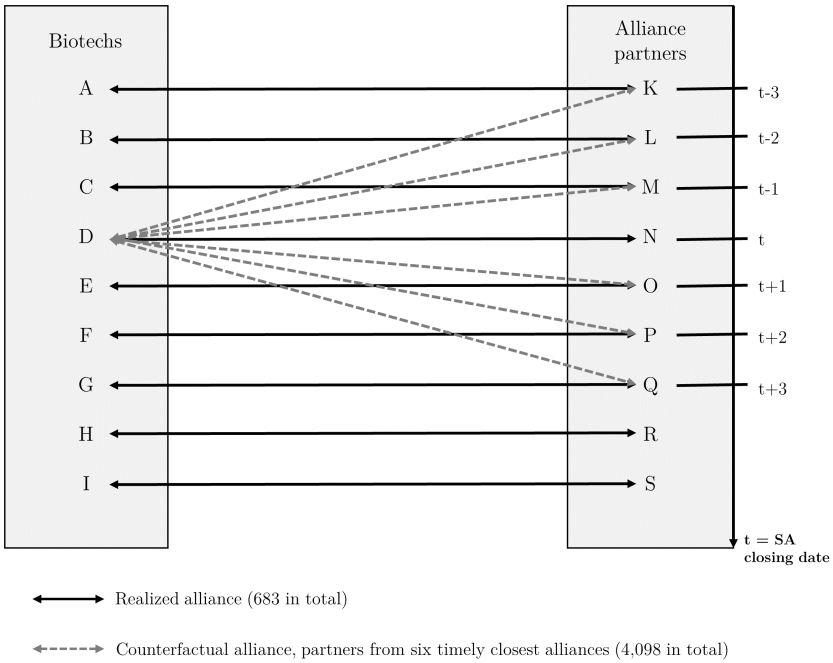

Figure 2.4. Construction of the counterfactual alliances sample

K, the next strategic alliance in the time sequence is B with L, and so on. We include all of these alliances in the sample of realized alliances. To explain how we construct the counterfactual matches to each of these realized alliances, we can take the (realized) alliance D-N as an example. As counterfactual matching partners to company D, we consider companies active as partners at the same time as company N, but that entered an alliance with a biotech company besides D. More specifically, we consider partners in the three closest strategic alliances formed prior and the three closest strategic alliances formed after the D-N alliance. These six partners (K, L, M, and O, P, Q) were potential partners of D. Thus, D-K, D-L, D-M, D-O, D-P, and D-Q are the counterfactual alliances to the realized D-N alliance. When we apply this procedure to all 683 realized alliances from our sample, we have 4,098 ($= 683 \cdot 6$) counterfactual alliances. We apply an alternative matching approach based on alliance characteristics rather than alliance timing in the robustness section.

2.4.2 Descriptive statistics for the realized and counterfactual alliances

This section compares the characteristics of the realized and counterfactual alliances. We start by focusing on whether the two companies that formed (or potentially could have formed) an alliance are both VC-backed. If they are both VC-backed, we are interested in two specific cases, i.e. whether they share the same VC or whether they were financed by connected VCs. Table 2.2 shows that out of the 683 realized strategic alliances, we have 388 pairs (56.8%) in which only the biotech company was VC-backed, and 295 pairs (43.2%) in which both partners were VC-backed. In the counterfactuals, we have 2,736 matches (66.8%) in which only the biotech is VC-backed and 1,362 matches (33.2%) in which both partners are VC-backed. The share of both-VC-backed pairs is significantly higher in the sample of realized alliances. We also observe significant differences in the share of the same-VC-backed alliances, which is 7.5% for realized alliances and only 3.3% for the counterfactual alliances. Table 2.2 reveals that the fraction of connected-VC-backed alliances differs between the samples of realized and counterfactual alliances. In 27.5% of realized alliances, but only in 18.2% of counterfactual alliances, connected VCs financed the alliance partners. The difference is statistically significant.

Besides using a dummy for connected VCs, we employ two alternative variables to capture the strength of the ties between the VCs that participate in the biotech company and those that finance the alliance partner. Imagine that we have three VCs in the biotech firm and three other VCs in the partner company. When we build all possible combinations between the biotech firm's VCs and the partner's VCs, we have nine VC-dyads. For each dyad, we count the number of all joint investments of these two VCs prior to the alliance closing date. Our first variable adds the ties for all nine dyads. We thus count the sum of all prior joint investments that any of the VCs backing the biotech firm made with any of the VCs participating in the partner company. If no joint investments occurred in the past (or if the partner company is non-VC-backed), then the number of joint investments equals zero. The number of all prior joint ties amounts to 17 ties in the realized sample and nearly 6 ties in the counterfactual alliances sample on

average, and the difference is statistically significant. Our second variable is the mean number of ties per VC-dyad. In the example above, we would divide the sum of the VC-dyad ties by 9. The mean number of ties per VC-dyad is significantly larger in realized sample than in the counterfactual alliances sample (0.20 and 0.08, respectively).[3] Consistent with the first measure, the second measure suggests that bilateral ties between VCs, which result from prior joint investments, are important in improving access to potential alliance partners.

In the next step, we compare proxies for transaction and information costs between realized and counterfactual alliances. We focus on geographical distance between alliance partners as well as their technological distance (same industry). We expect that with increasing distance, the transaction and information costs of forming and maintaining an alliance increase. The biotech company is located at a distance of 3,963 km from its partner on average in the sample of realized alliances. In the sample of counterfactual alliances, the geographical distance amounts to 4,109 km on average. The difference in means, however, is not statistically significant and the difference in medians is only weakly significant. We do not find statistically significant differences in the technological distance. The share of partners from the biotech industry is 20% in the realized sample and 21% in the counterfactual sample.

2.5 VC-dyad ties and strategic alliances

2.5.1 Total VC ties and alliance partner VC financing

We start by showing the link between VCs' connectedness and the probability that an alliance partner comes from a connected VC's portfolio. While all our biotech companies are VC-backed, their strategic alliance partners may be either VC-backed or non-VC-backed. As we showed in the last section, among the VC-backed partners, we can find partners backed by the same VC or by a connected VC. Based on these differences, we build a multinomial logistic model with four

[3]The mean is relatively small compared to the sum because the data are skewed. On the one hand, we observe many zeros and many small values, and on the other hand we find a few large syndicates of well-connected VCs.

categories of partners within the sample of all 683 realized alliances: non-VC-backed, VC-backed, same-VC-backed, and connected-VC-backed. In Table 2.3, we link the number of total VC ties to these four categories. The base category is an alliance with a non-VC-backed partner. Panel A shows the relative risk ratios (RRR). The results suggest that it is more likely that the biotech company enters in an alliance with a same-VC-backed or with a connected-VC-backed partner when the VCs that finance the biotech company have more ties. Panel B shows the average marginal effects. Stronger prior VC ties predict a higher likelihood of alliance formations in which both partners are either financed by the same VC or by connected VCs. The latter effect is larger (10.1 vs. 3.8 percentage points).

2.5.2 VC-dyad ties and alliance partner match

We proceed with the main part of the empirical analysis. We analyze whether companies backed by two different VCs have a higher likelihood to pair in an alliance if these two VCs have mutual connections. Thus, instead of total ties, we focus on bilateral ties within VC-dyads. More specifically, we investigate how the probability that a biotech company i and a partner j pair in an alliance is related to i and j having connected VCs. To deal with this probability, we employ cross-sectional logistic models within the sample of realized and counterfactual alliances. Our dependent variable is binary and takes the value one in the subsample of realized alliances; that is, when i and j pair in a strategic alliance. It equals zero in the subsample of counterfactual alliances. We expect the likelihood of pairing in a strategic alliance to increase when both companies are backed by connected VCs. To capture the effect of the specific VC-dyad and not the overall network effect, we control for the total VC ties. We also add VC similarity to proxy for the similarity in the degree of industry specialization of the VCs on both sides of the (potential) alliance. If both VCs have a similar degree of specialization, they will invest in similar companies, which, in turn, are more likely to form alliances with each other. Our VC similarity measure should control for this. Another control variable indicates whether the biotech company was involved in alliances in the past. Companies that formed alliances in the past are more likely to form alliances, regardless of whether they are connected through VC networks. Furthermore, we

employ other pair-specific characteristics. We also add year dummies to account for time-specific effects.

Table 2.4 presents the partial effects at the averages; that is, the marginal effects of each variable when we include the covariates at their sample means. In column (1), the positive marginal effect on the binary variable *Both VC-backed* suggests that the likelihood of forming an alliance increases when the potential strategic partner is VC-backed. We further see that an alliance is more likely to occur when the two VC-backed partners share the same VC than when they are financed by two different VCs. The probability is higher by 8.6 percentage points and the effect of the *Same-VC-backed* variable is significant at the 1% level. In columns (2) through (5), we focus on the connected-VC-effect. In column (2), the number of all prior joint ties among VCs that financed the biotech firm and those that backed the alliance partner is positive and statistically significant at the 1% level. An increase in the *VC-dyad ties* by one standard deviation corresponds to an increase in the alliance probability by 6.3 percentage points. Interestingly, when we include the two variables (*Same-VC-backed* and *VC-dyad ties*) jointly in column (3), the latter effect does not change in its magnitude and significance, while the *Same-VC-backed* effect gets much smaller and loses its statistical significance. These results uncover the important role that connected VCs play in alliance pairing. Prior studies conclude that when two companies share the same VC, the probability that these two companies close a strategic alliance is higher. Our results point out that bilateral VC ties are more beneficial for pairing in an alliance than having the same VC involved in both companies.

We perform a robustness check in columns (4) and (5). Here, we repeat the analyses from columns (2) and (3) with an alternative *VC-dyad ties* variable. Instead of summing up all mutual ties from all participating VC pairs, we include the average number of prior joint ties per VC-dyad. The results show that this variable is also statistically and economically significant. When we include the alternative *VC-dyad ties* variable together with the *Same-VC-backed* variable, the same-VC-effect becomes statistically and economically smaller than in column (1), but it remains significant. The *VC-dyad ties* effect does not change much.

We further conclude that the probability of pairing in an alliance decreases with increasing geographical distance between the partners. For technological distance,

we do not observe a significant negative effect. We rather observe a positive effect (significant at the 5% or 10% level), which suggests that a match between two companies is more likely if these companies are from different industries.[4] Companies probably use strategic alliances to diversify. VC similarity has, as expected, a positive effect on the probability of alliance formation.

As another robustness check, we construct an alternative counterfactual alliances sample. Our starting point is again the sample of 683 realized strategic alliances. From this sample, we create all possible combinations between biotech companies and their strategic alliance partners. In contrast with the main analysis, we do not limit the counterfactual sample to partners that close an alliance around the same time. Rather, every partner is a potential partner at any date between 2004 and 2016. Within this sample, we apply propensity score matching (PSM). To obtain the propensity scores, we estimate logistic regressions. As the explanatory variables, we employ the founding year of the biotech company and the strategic partner, the number of both companies' granted patents, a dummy variable that equals one if both partners are in the same (biotech) industry (and zero otherwise), as well as the continent on which the partner is located. Consistent with the main analysis, we generate a sample of counterfactual matches that is six times larger than the sample of realized alliances. We conditionally match six nearest neighbors to each realized alliance so that the biotech company in the counterfactual alliance pairs must be equal to the corresponding biotech company in the realized alliance pair.

Table 2.5 shows the results of the multivariate analyses with the alternative counterfactual alliances sample. We are interested in the partial effects at the averages of the *VC-dyad ties* in specifications (2) through (5).[5] In all four specifications, these effects are positive and statistically significant at the 1% level. Moreover, when we include the measure of VC-dyad ties jointly with the variable *Same-VC-backed* (columns (3) and (5)), the effect of the latter becomes insignificant in Column (3). To summarize, the results we obtain when using an alternative counterfactual alliances sample support the findings from the main analyses.

[4]This means that the strategic alliance partner not a biotech company because all our VC-backed companies are from the biotech industry.

[5]We include time fixed effects in all regressions. We do not employ the control variables from Table 2.4 because we include them in the PSM regressions.

2.5.3 VC-dyad ties and transaction and information costs

So far, we concluded that VC ties and their intensity are beneficial to alliance formation between portfolio companies of connected VCs. In the next step, we analyze whether connected VCs are more beneficial when transaction and information costs increase. To proxy for transaction and information costs, we employ geographical and technological distance. Other things being equal, the greater these distances are between two companies, the greater the transaction and information costs of pairing in an alliance are. To measure the connected-VC-effect at different levels of transaction and information costs, we include interaction terms between the two distance measures and our two alternative connected-VC measures. Consistent with the prior analyses, we are also interested in the same-VC-effect and we include the interaction terms of the distance measures with the same-VC-backed dummy.

Table 2.6 shows that same-VC-backing is beneficial in mitigating geographical distances.[6] The interaction term in column (1) has a positive sign and is statistically significant, supporting the view that the negative distance effect decreases when both partners share the same VC. We find a statistically significant effect for connected VCs in column (3), but not in column (5).

As to the technological distance, Table 2.4 suggests that a match between two companies is more likely if these companies are from different industries. In Table 2.6, we find that the probability that two companies from different industries pair in an alliance further increases when these companies were financed by VCs with closer ties. This effect holds for both of our alternative variables (see columns (4) and (6)). Typically, larger information asymmetries will accompany diversified alliances compared to focused alliances, but connected VCs seem to be able to reduce these asymmetries. Connected VCs thus help their portfolio companies overcome technological distance and enable them to better diversify into other sectors. We do not find a similar effect for companies that share the same VC (see column (2)).

[6]We run OLS regressions because the interpretation of the coefficients on interaction terms in non-linear models in not straightforward (Ai and Norton 2003; Williams 2009).

2.5.4 VC-dyad ties and IPO exit

Finally, we want to link the different alliance types to the likelihood of an IPO exit. The results in Table 2.7 suggest that companies with alliance partners from connected VCs' portfolios realize IPOs more often than other companies do. Column (2) suggests that having at least one alliance with a partner from a connected VC's portfolio increases the likelihood of an IPO by 26.9 percentage points. For comparison, having at least one alliance with a same-VC-backed partner is associated with a 14.7 percentage point increase, as column (1) shows. Furthermore, we check these results for robustness by altering the variables of interest. In column (3), we replace the same-VC-dummy by a variable that counts the number of common VCs in the alliance pair. When we increase this same-VC-variable by one standard deviation, the IPO probability increases by 8.8 percentage points. In column (4), we replace the connected-VC-backed dummy variable with the sum of all VC-dyad ties between VCs in the biotech company and the VCs in the alliance partner. A one-standard-deviation increase in the VC-dyad ties (sum) is associated with a 7.5 percentage point higher IPO probability. In addition, in columns (5) and (6), we replace the sum measures from columns (3) and (4) with average-per-alliance measures. We again find positive and statistically significant effects.

We then estimate two models in which we include the same-VC and connected-VC measures jointly. In column (7), we include the same-VC-backed dummy together with the sum of all VC-dyad ties between VCs in the biotech company and the VCs in the alliance partner. The same-VC-backed marginal effect becomes statistically insignificant, while the marginal effect of the VC-dyad ties stays statistically significant. In column (8), we employ the same-VC-backed dummy and the mean VC-dyad ties. The results again show that the same-VC-backed variable becomes statistically insignificant, while the average VC-dyad ties variable remains statistically significant.

These results indicate that alliances between the portfolio companies of connected VCs are associated with more successful companies.

2.6 Conclusion

This study advances our knowledge of how networks between financial intermediaries contribute to companies' development. We are the first to analyze how VC networks, grounded in prior bilateral cooperations between these investors, facilitate cooperation between portfolio companies from connected VCs' portfolios. By tracing individual VCs' investment and syndication histories, our analyses suggest that two companies whose VCs invested together in the past are more likely to enter a strategic alliance than other company pairs. We argue that VCs may be able to identify potential benefits from cooperation that might otherwise stay undetected because they have specific and detailed knowledge of the companies in their portfolios and they share this knowledge with their connected peers. Thus, they help reduce the search and transaction costs. We also suggest that for VCs and their portfolio companies, connected VCs may serve as a certification device that mitigates the information problems between involved alliance partners. Connected VCs may also mitigate moral hazard and expropriation risks. Our results support the conclusion that connected VCs are particularly beneficial when transaction and information costs are large. More specifically, the positive connected-VC-effect increases when geographical and technological distances become greater. Finally, we show that VC-backed companies that pair in alliances with partners financed by connected VCs realize IPOs more often. These results are robust to different specifications and methods of constructing the counterfactual sample. We also rule out alternative explanations. Our study thus documents a new channel through which portfolio companies benefit from ties among VCs.

An interesting issue for further investigations is how the time since VC funding affects the likelihood of forming an alliance. On the one hand, two companies in the current portfolios of two connected VCs may cooperate. On the other hand, a company formerly backed by a VC may form an alliance with a company from a connected-VC current or previous portfolio because the connected VC may still serve as a certification device. We expect the VC-effect to be especially strong when the companies are still in the VCs' portfolios, because in this case, the VCs have detailed information about the potential partners. In addition, when a company is still in the VC's portfolio, the VC typically exerts strong control, which will have

a disciplining effect on the company management not to engage in opportunistic behavior. It is on our future agenda to investigate how the connected-VC-effect evolves over time.

Another topic that deserves a deeper investigation is how the connected-VC-effect changes when information asymmetries and agency costs vary. While we demonstrate that the connected-VC-effect gets more important for companies that suffer from greater technological distances, further research should focus on institutional distance as well as on company-specific and industry-specific opacity. Finally, we only touched on the relationship between the connected-VC-participation and success. More research is required to improve our understanding of the mechanisms that drive this relationship.

Appendix 2.A: Tables

Table 2.1. Descriptive statistics

Panel A: Biotech companies

	Mean	Median	Min	Max	Std. dev.
Age	5.21	4.74	0.16	12.02	2.82
VC rounds	2.20	2.00	0.00	10.00	1.67
Patents	7.03	3.00	0.00	147.00	14.80
Investor count	4.40	3.00	1.00	21.00	3.57
Foreign VCs	0.32	0.29	0.00	1.00	0.26
VC experience	67.15	51.75	0.00	312.33	62.64
Total VC ties	255.11	203.40	0.00	1002.67	221.29
IPO dummy	0.24	0.00	0.00	1.00	-

Panel B: Strategic alliance partners

	Mean	Median	Min	Max	Std. dev.
Age	46.84	24.00	1.00	449.00	58.85
VC dummy	0.40	0.00	0.00	1.00	-
The following variables are calculated only for VC-backed strategic alliance partners					
VC rounds	3.34	2.00	1.00	24.00	3.18
Investor count	6.12	5.00	1.00	40.00	5.93
Foreign VCs	0.48	0.44	0.04	1.00	0.27
VC experience	74.99	53.05	0.00	638.00	86.47
Total VC ties	235.67	196.58	0.00	911.67	204.38
Industries:					
Biotech	20.12%				
Pharma	22.13%				

Legend: This table presents the descriptive statistics for the biotech companies and their strategic alliance partners. The statistics, except the *IPO dummy*, are calculated at the time of the biotech firm's first strategic alliance (Panel A) or at the time of the partner's first alliance (Panel B). *Age* represents the company age (in years). *VC dummy* is a dummy variable that equals one if the strategic alliance partner is VC-backed. *VC rounds* counts the number of VC investment rounds in the company. *Investor count* is the number of involved VCs. *Foreign VCs* is the fraction of non-US VCs. *VC experience* is the number of all prior portfolio companies of the involved VCs (average per VC). *Total VC ties* is the number of all prior syndicate partners of the involved VCs (average per VC). *Patents* is the number of patent applications. *IPO dummy* is a dummy variable that equals one if the biotech company went public.

Table 2.2. Realized and counterfactual alliances

	Count	Non-VC	Both VC-backed	Same-VC-backed	Connected-VC-backed (dummy)	VC-dyad ties (sum)	VC-dyad ties (mean)	Distance	Same industry	Age difference
(1) Realized alliances	683	388	295	51	188	17.00	0.20	3,963	0.20	47.13
... *percent*		56.8%	43.2%	7.5%	27.5%					
(2) Counter-factual alliances	4,098	2,736	1,362	135	745	5.95	0.08	4,109	0.21	39.93
... *percent*		66.8%	33.2%	3.3%	18.2%					
t-value		-5.075***		-5.235***	-5.724***	-9.710***	-8.086***	0.9727	0.218	-3.557***
z-value		-5.062***		-5.221***	-5.705***	-6.502***	-6.398***	1.751*	0.218	-4.401***

Legend: *Count* is the number of realized and counterfactual alliances. *Non-VC* is the number of alliances in which the alliance partner is not VC-backed. *Both VC-backed* counts the number of alliances in which both partners are VC-backed. *Same-VC-backed* is the number of alliances in which both partners share at least one common VC. *Connected-VC-backed* counts the number of alliances in which the two partners obtain financing from connected VCs. *VC-dyad ties (sum)* is the sum of all ties (i.e., prior common investments) between the VCs in the biotech company and the VCs in the alliance partner. *VC-dyad ties (mean)* is the mean number (per VC-dyad) of ties between the VCs in the biotech company and the VCs in the alliance partner. *Distance* is the geographical distance between the alliance partners (in km). *Same industry* is a dummy variable that equals one if both alliance partners operate in the same industry, and zero otherwise. *Age difference* is the mean of the difference in ages between both partners. t-value refers to the mean difference test between (2) and (1). z-value refers to the rank-sum test. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.3. Multinomial logistic regressions: Realized alliances

	Panel A: RRR – Category 1: Non-VC (base)			**Panel B:** Average marginal effects			
	Cat.2 Both VC-backed	Cat.3 Same-VC-backed	Cat.4 Connected-VC-backed	Cat.1 Non-VC	Cat.2 Both VC-backed	Cat.3 Same-VC-backed	Cat.4 Connected-VC-backed
Total VC ties	0.8204*	2.8753***	2.3768***	-0.1007***	-0.0387***	0.0384***	0.1011***
	(0.0944)	(0.6170)	(0.3056)	(0.0152)	(0.0074)	(0.0117)	(0.0159)
VC similarity	1.0496***	1.1056***	1.0622***	-1.0829***	0.1926***	0.3949***	0.4954***
	(0.0085)	(0.0168)	(0.0078)	(0.0699)	(0.0517)	(0.0872)	(0.0928)
Foreign VCs	1.0293***	1.0433***	1.0332***	-0.0057***	0.0013***	0.0014***	0.0030***
	(0.0067)	(0.0098)	(0.0063)	(0.0008)	(0.0004)	(0.0005)	(0.0008)
Investor count	0.8125***	1.1584***	1.0721**	0.0002	-0.0182***	0.0079***	0.0101***
	(0.0450)	(0.0479)	(0.0296)	(0.0045)	(0.0041)	(0.0022)	(0.0036)
Alliance count	0.8823**	0.9625	0.9957	0.0077	-0.0093**	-0.0015	0.0031
	(0.0519)	(0.0502)	(0.0314)	(0.0051)	(0.0044)	(0.0030)	(0.0044)
Distance	0.9304	0.9490	0.9054**	0.0147**	-0.0032	0.0003	-0.0118*
	(0.0620)	(0.0850)	(0.0455)	(0.0075)	(0.0049)	(0.0051)	(0.0070)
Patents	1.3986**	0.7908	0.8497*	0.0047	0.0304***	-0.0111	-0.0239*
	(0.1898)	(0.1173)	(0.0830)	(0.0145)	(0.0100)	(0.0082)	(0.0131)
N	683	683	683	683	683	683	683

Legend: Panel A presents the relative risk ratios (RRR) for the multinomial logistic regressions and Panel B reports the average marginal effects. The dependent variable is categorical and equals one if the strategic partner is not VC-backed, two if both partners are VC-backed, three if both partners share a common VC, and four if the two partners obtained financing from VCs that invested together in the past. *Total VC ties* measures the (log) mean number of prior syndicate partners of the VCs involved in the biotech firm. *VC similarity* is the similarity in the biotech or pharma specialization between the involved investors, calculated as the absolute difference in specialization multiplied by minus one (in means). *Foreign VCs* is the share of non-US VCs involved in the biotech firm. *Investor count* is the number of VCs in the biotech firm. *Alliance count* is the sequence of the particular alliance of the biotech firm. *Distance* is the (log) geographical distance between the two strategic partners. *Patents* is the (log) number of the biotech company's patent applications. A constant is included in all regressions. Robust standard errors are displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.4. Logistic regressions: Realized and counterfactual alliances

DV: Realized alliance	(1)	(2)	(3)	(4)	(5)
Same-VC-backed	0.0859***		0.0032		0.0450**
	(0.0226)		(0.0274)		(0.0226)
VC-dyad ties (sum)		0.0068***	0.0068***		
		(0.0008)	(0.0009)		
VC-dyad ties (mean)				0.2853***	0.2610***
				(0.0510)	(0.0516)
Total VC ties (sum)	0.0000	-0.0001***	-0.0001***		
	(0.0000)	(0.0000)	(0.0000)		
Total VC ties (mean)				-0.0065	-0.0069*
				(0.0040)	(0.0040)
VC similarity (sum)	0.0024***	0.0021***	0.0021***		
	(0.0006)	(0.0006)	(0.0006)		
VC similarity (mean)				0.0802***	0.0779***
				(0.0265)	(0.0265)
Both VC-backed	0.0627***	0.0440***	0.0439***	0.0141	0.0108
	(0.0122)	(0.0119)	(0.0119)	(0.0120)	(0.0121)
Previous alliances (dummy)	0.0037	0.0024	0.0024	0.0004	0.0003
	(0.0112)	(0.0110)	(0.0110)	(0.0116)	(0.0116)
Distance	-0.0110***	-0.0109***	-0.0109***	-0.0103***	-0.0102***
	(0.0027)	(0.0027)	(0.0027)	(0.0028)	(0.0028)
Same industry	-0.0127	-0.0244**	-0.0244**	-0.0221*	-0.0223*
	(0.0124)	(0.0119)	(0.0119)	(0.0127)	(0.0127)
Age difference	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Patents	0.0023	0.0008	0.0008	-0.0012	-0.0011
	(0.0043)	(0.0043)	(0.0043)	(0.0045)	(0.0045)
Year Dummies	Yes	Yes	Yes	Yes	Yes
N	4,781	4,781	4,781	4,781	4,781

Legend: This table presents the partial effects at the averages from the logistic regressions with the dependent variable *realized alliance*, which is a dummy variable that equals one if an alliance was realized, and zero for counterfactual alliances. *Same-VC-backed* is a dummy variable that equals one if both alliance partners share a common VC, and zero otherwise. *VC-dyad ties (sum)* is the (log) total number of ties between the VCs in the biotech company and the VCs in the alliance partner. *VC-dyad ties (mean)* is the (log) mean number (per VC-dyad) of ties between the VCs in the biotech company and the VCs in the alliance partner. *Total VC ties (sum)* is the (log) total number of all prior syndicate partners of the VCs involved in the biotech firm. *Total VC ties (mean)* is the (log) mean number of all prior syndicate partners of the VCs involved in the biotech firm. *VC similarity (sum)* is the similarity in the biotech or pharma specialization between the involved investors, calculated as the absolute difference between the sum of the specialization of the involved investors multiplied by minus one. *VC similarity (mean)* is the similarity in the biotech or pharma specialization between the involved investors, calculated as the absolute difference between the means of the specialization of the involved investors multiplied by minus one. *Both VC-backed* is a dummy variable that equals one if both partners are VC-backed, and zero otherwise. *Previous alliances (dummy)* is a dummy variable that equals one if the biotech company engaged in previous alliances, and zero otherwise. *Distance* is the (log) geographical distance between the two strategic partners. *Same industry* is a dummy variable that equals one if both partners operate in the same industry, and zero otherwise. *Age difference* measures the difference in the ages of both alliance partners. *Patents* is the (log) number of the biotech company's patent applications. A constant is included in all regressions. Robust standard errors are displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.5. Logistic regressions: Realized and counterfactual alliances (with PSM)

DV: Realized alliance	(1)	(2)	(3)	(4)	(5)
Same-VC-backed	0.0792***		0.0405		0.0721***
	(0.0242)		(0.0276)		(0.0230)
VC-dyad ties (sum)		0.0023***	0.0019***		
		(0.0005)	(0.0006)		
VC-dyad ties (mean)				0.1135***	0.0883***
				(0.0290)	(0.0301)
Total VC ties (sum)	0.0001***	0.0000	0.0000		
	(0.0000)	(0.0000)	(0.0000)		
Total VC ties (mean)				-0.0046	-0.0050
				(0.0041)	(0.0041)
VC similarity (sum)	0.0015**	0.0014**	0.0014**		
	(0.0006)	(0.0007)	(0.0007)		
VC similarity (mean)				0.0596**	0.0550**
				(0.0267)	(0.0267)
Both VC-backed	0.0239**	0.0211*	0.0199*	0.0105	0.0064
	(0.0118)	(0.0118)	(0.0118)	(0.0119)	(0.0120)
Previous alliances (dummy)	-0.0018	-0.0029	-0.0028	-0.0024	-0.0026
	(0.0113)	(0.0113)	(0.0113)	(0.0113)	(0.0113)
Year Dummies	Yes	Yes	Yes	Yes	Yes
N	4,781	4,781	4,781	4,781	4,781

Legend: This table presents the partial effects at the averages from the logistic regressions with the dependent variable *realized alliance*, which is a dummy variable that equals one if an alliance was realized, and zero for counterfactual alliances. The sample of counterfactual alliances comes from a propensity score matching. *Same-VC-backed* is a dummy variable that equals one if both alliance partners share a common VC, and zero otherwise. *VC-dyad ties (sum)* is the (log) total number of ties between the VCs in the biotech company and the VCs in the alliance partner. *VC-dyad ties (mean)* is the (log) mean number (per VC-dyad) of ties between the VCs in the biotech company and the VCs in the alliance partner. *Total VC ties (sum)* is the (log) total number of all prior syndicate partners of the VCs involved in the biotech firm. *Total VC ties (mean)* is the (log) mean number of all prior syndicate partners of the VCs involved in the biotech firm. *VC similarity (sum)* is the similarity in the biotech or pharma specialization between the involved investors, calculated as the absolute difference between the sum of the specialization of the involved investors multiplied by minus one. *VC similarity (mean)* is the similarity in the biotech or pharma specialization between the involved investors, calculated as the absolute difference between the means of the specialization of the involved investors multiplied by minus one. *Both VC-backed* is a dummy variable that equals one if both partners are VC-backed, and zero otherwise. *Previous alliances (dummy)* is a dummy variable that equals one if the biotech company engaged in previous alliances, and zero otherwise. A constant is included in all regressions. Robust standard errors are displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.6. OLS regressions with realized and counterfactual alliances (interaction effects)

DV: Realized alliance	(1)	(2)	(3)	(4)	(5)	(6)
Same-VC-backed	-0.1357	0.1179**				
	(0.1047)	(0.0458)				
VC-dyad ties (sum)			0.0028	0.0105***		
			(0.0037)	(0.0011)		
VC-dyad ties (mean)					0.0480	0.5551***
					(0.2743)	(0.1198)
Total VC ties (sum)	0.0000	0.0000	-0.0000***	-0.0001***		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
Total VC ties (mean)					-0.0073*	-0.0075*
					(0.0042)	(0.0042)
VC similarity (sum)	0.0012***	0.0013***	0.0008***	0.0008***		
	(0.0002)	(0.0002)	(0.0002)	(0.0002)		
VC similarity (mean)					0.0758***	0.0756***
					(0.0255)	(0.0255)
Both VC-backed	0.0577***	0.0576***	0.0342***	0.0314**	0.0083	0.0047
	(0.0123)	(0.0123)	(0.0123)	(0.0122)	(0.0126)	(0.0127)
Distance	-0.0141***	-0.0119***	-0.0144***	-0.0126***	-0.0134***	-0.0114***
	(0.0035)	(0.0035)	(0.0036)	(0.0034)	(0.0037)	(0.0035)
Same industry	-0.0134	-0.0135	-0.0236*	-0.0103	-0.0223*	-0.0116
	(0.0132)	(0.0133)	(0.0130)	(0.0135)	(0.0132)	(0.0137)
Same-VC-backed	0.0347**					
x Distance	(0.0145)					
Same-VC-backed		-0.0151				
x Same industry		(0.0675)				
VC-dyad ties (sum)			0.0007*			
x Distance			(0.0004)			
VC-dyad ties (sum)				-0.0044***		
x Same industry				(0.0016)		
VC-dyad ties (mean)					0.0507	
x Distance					(0.0367)	
VC-dyad ties (mean)						-0.2415*
x Same industry						(0.1468)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	4,781	4,781	4,781	4,781	4,781	4,781

Legend: This table presents the results of the OLS regressions with interaction effects. The dependent variable is *realized alliance*, which is a dummy variable that equals one if an alliance was realized, and zero for counterfactual alliances. *Same-VC-backed* is a dummy variable that equals one if both alliance partners share a common VC, and zero otherwise. *VC-dyad ties (sum)* is the (log) total number of ties between the VCs in the biotech company and the VCs in the alliance partner. *VC-dyad ties (mean)* is the (log) mean number (per VC-dyad) of ties between the VCs in the biotech company and the VCs in the alliance partner. *Total VC ties (sum)* is the (log) total number of all prior syndicate partners of the VCs involved in the biotech firm. *Total VC ties (mean)* is the (log) mean number of all prior syndicate partners of the VCs involved in the biotech firm. *VC similarity (sum)* is the similarity in the biotech or pharma specialization between the involved investors, calculated as the absolute difference between the sum of the specialization of the involved investors multiplied by minus one. *VC similarity (mean)* is the similarity in the biotech or pharma specialization between the involved investors, calculated as the absolute difference between the means of the specialization of the involved investors multiplied by minus one. *Both VC-backed* is a dummy variable that equals one if both partners are VC-backed, and zero otherwise. *Distance* is the (log) geographical distance between the two strategic partners. *Same industry* is a dummy variable that equals one if both partners operate in the same industry, and zero otherwise. We also control for the difference in the ages of both alliance partners, the number patent applications of the biotech company, and for previous alliances (dummy). In addition, we include year dummies and a constant in all regressions. Robust standard errors are displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.7. Logistic regressions with company exits

DV: IPO dummy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Both VC-backed	0.0839	-0.1076	0.0894	0.0996	0.0874	0.0414	0.0761	0.0307
	(0.0704)	(0.1320)	(0.0688)	(0.0668)	(0.0694)	(0.0724)	(0.0699)	(0.0741)
Same-VC-backed (dummy)	0.1471**						0.1043	0.0784
	(0.0728)						(0.0770)	(0.0786)
Connected-VC-backed (dummy)		0.2693**						
		(0.1247)						
Same-VC-backed (sum)			0.0649***					
			(0.0203)					
VC-dyad ties (sum)				0.0004**			0.0003*	
				(0.0002)			(0.0002)	
Same-VC-backed (mean)					0.1142**			
					(0.0545)			
VC-dyad ties (mean)						0.0017**		0.0015*
						(0.0008)		(0.0008)
Patents (sum)	0.0019*	0.0019*	0.0022**	0.0018*	0.0020*	0.0014	0.0019*	0.0015
	(0.0011)	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0011)	(0.0012)
Foreign VCs (dummy)	0.2180**	0.2242**	0.2141**	0.2591**	0.2145**	0.2375**	0.2397**	0.2274**
	(0.1012)	(0.0981)	(0.1023)	(0.1085)	(0.1029)	(0.1023)	(0.1066)	(0.1025)
Alliance count (sum)	-0.0797	-0.0707	-0.0989	-0.1300*	-0.0457	-0.0456	-0.1313*	-0.0605
	(0.0622)	(0.0633)	(0.0621)	(0.0705)	(0.0631)	(0.0602)	(0.0722)	(0.0618)
N	202	202	202	202	202	202	202	202

Legend: This table presents the partial effects at the averages from the logistic regressions with the dependent variable *IPO dummy*, which equals one if the company went public, and zero otherwise. *Both VC-backed* is a dummy variable that equals one if the biotech company had at least one alliance in which both partners were VC-backed, and zero otherwise. *Same-VC-backed (dummy)* is a dummy variable that equals one if there was at least one common VC in the biotech company and any of its strategic alliance partners, and zero otherwise. *Same-VC-backed (sum)* and *Same-VC-backed (mean)* represent the sum or mean of the *Same-VC-backed (dummy)* over all realized alliances of the biotech company. *Connected-VC-backed (dummy)* is a dummy variable that equals one if the company had at least one alliance in which both partners obtained financing from connected VCs (i.e., had prior common investments), and zero otherwise. *VC-dyad ties (sum)* and *VC-dyad ties (mean)* represent the (log) sum or mean of all ties (i.e., prior common investments) between the VCs in the biotech company and the VCs in the alliance partners. *Patents (sum)* is the (log) number of the biotech company's patent applications. *Foreign VCs (dummy)* is a dummy variable that equals one if there was at least one non-US VCs involved in the biotech firm. *Alliance count (sum)* is the (log) number of all alliances of the biotech firm. A constant is included in all regressions. Robust standard errors are displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Chapter 3

The Role of Strategic Alliances in VC Exits: Evidence from the Biotechnology Industry[1]

Abstract

This study contributes to a better understanding of the relationship between strategic alliances and VC exits. The recent empirical literature concludes that alliances improve the probability of successful exits (IPOs and M&As) for venture-backed companies. When we control for observed and unobserved heterogeneity in a cohort sample of companies, for the self-selection into alliance activity, and for censoring, we find a smaller effect than prior studies do. Moreover, we confirm the positive effect of alliances only for IPOs, but not for M&As. These findings are consistent with the view that strategic alliances help companies certify their quality for potential buyers.

JEL *classification:* G24, L24, L26

[1]This is an Author's Original Manuscript of an article published by Taylor & Francis Group in Venture Capital available online at `https://www.tandfonline.com/doi/full/10.1080/13691066.2020.1814192`. Earlier versions of this chapter were presented at the Academy of Entrepreneurial Finance Conference 2017, 14th Edition of the Augustin Cournot Doctoral Days, Emerging Trends in Entrepreneurial Finance Conference, and 3rd Entrepreneurial Finance Conference.

3.1 Introduction

In the financing of promising start-ups, it is difficult to disentangle bad intentions from bad luck. As technologies become more complex, agency problems become more exacerbated. Because future outcomes are distant and unpredictable, entrepreneurs and their financiers are plagued by uncertainty about future prospects, and separating the root cause of failure (intentional or unintentional) might be infeasible. In fact, venture capital (VC) firms face high levels of uncertainty and entrepreneurs may defect without being detected. When it comes to overcoming the involved agency problems vis-à-vis the entrepreneur, financiers such as VC firms use several checks and balances (Kaplan and Strömberg 2003).

Yet, what happens when VC firms themselves are about to exit the investment, whether through an initial public offering (IPO) or a merger/acquisition (M&A)? The decision to exit an investment will raise eyebrows among potential buyers about the underlying quality of the transaction they are about to enter (Cumming 2008). Not surprisingly, the absence of sufficient collateral and the high asset-specific knowledge exacerbates the bilateral dependency of VC firms and potential buyers. In instances like these, the information available about the quality of a project differs between the seller(s) and the buyer(s). In general, the party making the buying decision possesses less information. Certification through a third party is one way to mitigate the information asymmetry between contracting parties. In this study, we ask whether strategic alliances may serve as a certifying device and whether their role differs based on the type of exit (IPO vs. M&A).

We contribute to several strands of literature. We add to the literature on the role of strategic alliances in VC-backed companies and how they are related to exits (see, e.g., Lindsey 2008; Ozmel et al. 2013b; Wang et al. 2012). Strategic alliances can reduce information asymmetries between the company and potential buyers, and thus positively affect the chances for a successful exit. While prior studies do not deal with differences between different types of exits, we argue that the alliance effect may vary with the type of exit.

Our work contributes to studies that highlight the distinctions between different exit routes. While most studies proxy VC success with a binary variable *successful exit* equal to one if the company performs an IPO or was a target in a successful

M&A transaction (Hochberg et al. 2007; Hochberg 2012), several works point out differences between these two exit channels (see, e.g., Cumming and Johan 2008; Giot and Schwienbacher 2007). Cumming and Johan (2008) argue that IPOs will be the most difficult exit choice for VC firms because they need to mitigate the highest risk of asymmetric information. When companies go public, many potential buyers exist and a single buyer faces the free riding problem, which reduces their incentive to collect information. In this situation, a potential uninformed buyer may interpret it as another company being willing to form a strategic alliance with a particular company as a certification of quality. Before acquisitions, the single acquiring party will have incentives to conduct deep due diligence. Consequently, we argue that IPO and M&A exits have different needs for certification. Therefore, we expect that alliances are an important certification device before IPOs, and that they are less important before M&As.

Regarding M&As, Ozmel et al. (2013b) argue that strategic alliances increase the likelihood of a subsequent M&A transaction for reasons other than certification. One reason they suggest is that strategic partners, as insiders, may themselves take over the VC-financed companies. Consequently, we should expect a positive association between strategic alliances and M&As. However, they do not document how often this scenario happens in reality. In our sample of 663 companies, we track the buyers' identity and find only four cases in which the strategic alliance partner took over the VC-financed company. That is, the case that Ozmel et al. (2013b) describe is rare, and presents merely anecdotal evidence.[2] Hagedoorn and Sadowski (1999) also point out that these cases are exceptions: "[...] that the transformation from strategic technology alliances to merger and acquisitions hardly ever takes place." Thus, we expect that strategic alliances are less important for the success of an M&A exit compared to an IPO exit.

This study also adds to research that deals with VC exits and certification. The literature provides conflicting evidence on the role of VC firms when taking companies public. Early works such as that by Megginson and Weiss (1991) conclude that VC firms may certify the quality of their portfolio companies when they take them public. More recent studies fail to find evidence in favor of certification

[2]The results in our study do not change when we exclude these four observations from the sample.

effects, but rather attest to VC firms' conflicts of interest upon exiting (see, among others, Lee and Wahal 2004). Therefore, the role of VC firms as a certification device is at least questionable. Recent works also question the validity of patents as certification devices for underlying company quality and argue that more market-based devices such as strategic alliances could attest to company quality (Hoenig and Henkel 2015). Deeds et al. (1997) find that IPO success is positively related to credible signals that indicate the value of the firm's intangible assets. However, their study does not focus on strategic alliances, but rather on R&D spending, patents, quality of the research staff, or the number of products under development. Other studies (Khoury et al. 2013; Koka and Prescott 2002; Payne et al. 2011) support the view that strategic alliances may serve as a signal to external resource providers.

Our study also provides a methodological contribution. Unlike in experimental studies (such as Hoenig and Henkel 2015), violations of the strict exogeneity assumption may lead to biased estimates. As such, we need to level out the effect of variables on the likelihood of entering strategic alliances and the impact of these variables on the exit to arrive at unbiased estimates. We first employ a cohort study of 663 US-based biotech ventures founded between 2004 and 2008. Hence, these ventures we set up under similar regulatory and economic environments. The random sampling based on the foundation year also alleviates the concerns of left censoring, in which companies are prone to heterogeneity in terms of the development stage. Second, we use a host of control variables to control for other observable characteristics that affect both the chances to form a strategic alliance and to exit successfully. We employ lagged variables to deal with potential reverse causation. Third, we apply different approaches that account for unobserved heterogeneity to infer the causal effect of strategic alliances on the chances of exit. We start by employing company and time fixed effects. The former ensures that we eliminate time-invariant characteristics at the company level, while the latter allows us to account for changes in economic conditions. We then complement these findings with results from a propensity score matching approach that controls for potential endogeneity in the choice for or against a strategic alliance.

We believe that VC-backed biotechnology companies are the ideal setting to investigate whether strategic alliances are associated with certification for poten-

tial buyers at the exit because these companies face a long product development cycle with substantial risks and uncertainties. At the same time, VC firms want to realize fast exits because they are under pressure to return funds to their investors. Finally, strategic alliances can serve as a certification device since others can observe alliance formation and positive abnormal returns are documented around the announcement of these events (Anand and Khanna 2000; Stuart 1998).

Our new findings to the literature on the role of strategic alliances in exits in VC-backed companies are threefold. First, we find that strategic alliances have different effects for different types of exit. More specifically, we confirm a positive effect of strategic alliances only for IPOs, but not for M&As. Second, the magnitude of the alliance effect is less than that reported in prior studies. Third, we challenge the pervasive assumption of temporally constant effects. While the overall effect on M&As is insignificant, it is negative in the short term and turns positive in the long term.

The rest of the paper is organized as follows. We present the theoretical background in section 3.2. Section 3.3 describes our dataset and variables. Afterwards, we discuss the methodology in section 3.4. Section 3.5 presents the results. Finally, in section 3.6, we discuss the main findings, possible implications, and limitations of this study.

3.2 Theoretical background

When taking a company public, incumbent investors generally have an informational advantage over potential buyers (Allen and Faulhaber 1989; Welch 1989), who have to rely on the information that incumbents provide. While incumbent investors may engage in road shows and provide gloomy outlooks, talk is literally cheap. The incumbents' self-interests and information asymmetries can work to the detriment of potential buyers that are expected to inject new cash into the business in exchange for the incumbents' value-creation promise.

The problem of uncertainty regarding company quality is pronounced for young biotechnology companies. A typical biotechnology company faces a long product development cycle, usually 7 to 10 years, as the company advances from the first idea through clinical trials and the FDA approval process (Deeds et al. 1997).

During this time, the outcome is uncertain, the company needs cash, and does not generate any revenue. Given the intangible nature of knowledge and the absence of collateral, substantial uncertainty persists. It is therefore difficult for potential buyers to judge whether such a company will succeed in advancing products through the long development cycle to generate revenues.

For potential buyers in an IPO, the availability of information is one of the key determinants of subsequent resource allocation. Therefore, positive information from a credible third party will play a crucial role in reducing information asymmetries and mitigating potential agency conflicts (Bushman et al. 2004). Without such information, new buyers may fear that they will invest in low-quality companies.

As such, the literature discusses several certification devices that companies can provide to reduce information asymmetry in the course of an IPO. The presence of a reputable VC may ensure that a young company is not holding back IPO-relevant information (Megginson and Weiss 1991), though the incentives of the selling VC firms create grounds for adverse selection (Lee and Wahal 2004). Daily et al. (2003) review possible variables related to IPO quality, such as company size, auditor reputation, and VC backing. Basdeo et al. (2006) argue that market participants observe the strategic actions of focal companies and form expectations of abilities and reputations. One of the strongest quality indicators that IPO participants may receive is the ability of another company to attest to the quality of the underlying company in which they are about to invest. Stuart et al. (1999) and Chen et al. (2008) argue that companies affiliate with a prominent partner to signal their company value. Hoenig and Henkel (2015) suggest that strategic alliances are more reflective of the companies' underlying technological advantage than are patent grants.

We therefore expect that a VC-financed company's behavior in the form of a strategic alliance reveals unobservable technological attributes. Strategic alliances convey positive information that reflect the strategic goals, intentions, and abilities of VC-financed companies to outsiders (Basdeo et al. 2006; Milgrom and Roberts 1986). Hence, a strategic alliance attests to the underlying quality of the company and improves its chances to go public.

In IPOs, individual investors face the free riding problem. Because information

is costly to obtain, a single investor does not have incentives to collect information and the market could break down. For the market to operate, the certification of the IPO quality through a third party would be beneficial. A strategic alliance with a third party may provide such a certification. An uninformed investor may interpret it as another company being willing to form a strategic alliance with a particular company as a certification of quality. The situation in M&A exits is different. Before an acquisition, there are only a few potential buyers (or in some cases, only a single buyer). M&A transactions are subject to severe scrutiny by potential buyers and involve due diligence procedures and multi-round negotiations (or auctioning). Hence, instead of relying on outside certification, acquirers screen the target themselves. Consequently, we argue that IPO and M&A exits have different needs for certification. While being important for IPO exits, strategic alliances may be irrelevant as a quality indicator in M&A exits.

In addition, Cumming (2008) argues that if VC firms have weaker control rights, the likelihood of an IPO is higher than that of an M&A. Strategic alliances might lead to more involved interests, and hence, to weaker VC control rights. This would mean that for companies with strategic alliances, VC firms tend to exit via an IPO rather than via an M&A.

Finally, in the short-term, the exit motives might be at odds with the intentions of existing strategic alliance partners. This may create conflicts between the project-level decision (and cash flow) rights of existing alliance partners and potential acquirers (Robinson and Stuart 2007b), leading to a preference for an IPO over an M&A. We therefore argue that if a VC-financed company entered a strategic alliance, the likelihood of that company being acquired through an M&A transaction is bound to be lower than the likelihood of going public.

3.3 Data

3.3.1 Sample

Our sample consists of 663 US VC-backed biotechnology companies founded between 2004 and 2008. We draw this sample of companies from Dow Jones VentureSource and from the Thomson One database. We employ all available records for

VC-backed companies in the biotechnology sector from the combination of these two databases. We exclude companies that did not disclose the VC investors and eliminate duplicate entries.

Our aim is to create a homogeneous sample (in terms of company age and industry) that we subsequently track over time. This type of cohort study reduces concerns about unobserved heterogeneity due to the firms being at different development stages. With this design, we also remove concerns about left censoring. Because we observe all companies from their birth, there are no relevant events before the study enrollment.

For these companies, we track their strategic alliance activity, VC financing, patenting, and exits until 2014. We extract information about strategic alliances from S&P Capital IQ, which defines a strategic alliance as a "relationship between two or more companies to pursue a common objective through mutual cooperation, pooling of resources, etc.".[3] Data on VC financing and exits come from Dow Jones VentureSource and from the Thomson One database. We employ data on patents from Patstat. We use the online access to Patstat of the European Patent Office (EPO) and collect information about patents by both the application and publication dates.

3.3.2 Dependent variables: IPO exit and M&A exit

We are interested in understanding the role of strategic alliances in VC exits. Following much of the literature (e.g., Das et al. 2011; Dai et al. 2012; Hochberg et al. 2007; Nahata et al. 2014; Sørensen 2007), we assume that VC firms aim to exit their companies either via an IPO or an M&A. Table 3.1 shows that 78 companies were taken public and 99 companies were exited via an M&A. If a company was not exited by 2014, we treat it as unsuccessful. This approach is common in studies that rely on commercial databases that are likely to underreport bankruptcies (generally, participants have a higher reluctance to report this instance appropriately).

[3]We explicitly exclude joint ventures and other business relationships such as licensing, distribution, or franchising. Some other commercial databases have different definitions of strategic alliances that also include stakeholder alliances such as cooperation with suppliers or customers, as strategic alliances.

We define two dependent variables. If a company went public in a particular year, then the dummy variable *IPO exit* equals one in that year and in all succeeding years (and zero otherwise). The second dependent variable *M&A exit* equals one if the company exited through M&A and is equal to one in all succeeding years (and zero otherwise).

The problems with truncation and censoring has been well documented in the literature on strategic alliances and VC exits (Ozmel et al. 2013b; Yang and Aldrich 2012). The problem of right censoring is that a sample could end before we can observe a future exit event. To ensure that we did not introduce an artificial bias into our analysis, we follow previously published work in this area. For example, Nahata (2008) uses an investment sample ending in 2001 and classifies all companies that did not exit successfully by the beginning of 2006 as unsuccessful exits. Hochberg et al. (2007) assume that a company for which they found no information about an exit at the fund's tenth anniversary was liquidated. Our success rate is comparable to those reported in prior studies. In total, 26.7% of companies from our sample had successful exits. This percentage is within the range reported in recent studies; for example, Nahata et al. (2014) report 24.2% and Ozmel et al. (2013b) state 30.6%. Nevertheless, we provide additional analyses in the robustness section to ensure that we do not underreport successful exits.

3.3.3 Independent variables

Our main independent variables are related to the companies' involvement in strategic alliances. In our regressions, we also include other variables that may be used as certification devices (such as patents) at the exit as well as further controls.

Our sample companies were involved in 578 strategic alliances (see Table 3.1). The average number of strategic alliances per company is 0.87 for the whole sample and 2.5 alliances among companies with at least one alliance. As Table 3.1 shows, the distribution of the number of strategic alliances is heavily right-skewed; 64.7% of companies have no alliances. The median number of strategic alliances of the companies that have at least one alliance is two. Table 3.1 also demonstrates that companies that enter at least one strategic alliance have a higher likelihood of

an IPO than companies without strategic alliances (21.4% vs. 6.5%), while the likelihood of an M&A is almost the same (close to 15%). In the next sections, we elaborate on these first insights with multivariate analyses.

We include two types of strategic alliance measures in our analyses. First, we generate a variable that counts the number of strategic alliances. Second, we create a dummy variable that indicates whether a company had any strategic alliances. In addition, we include variations of these two variables for the time periods in which the companies formed their strategic alliances.

Our sample companies applied for 4,531 patents and were granted 3,342 patents. Companies that do not have any strategic alliance were granted 3.44 patents on average and companies with at least one alliance were granted 7.97 patents on average (see Table 3.1).

In our regressions, we also control for VC investment characteristics. Along with the total number of involved VC firms, we include a variable that counts the number of new VC firms. A higher number of VC firms may have a positive effect, as more VC firms may add higher value. However, syndication, especially for VC firms that joined recently, might lead to conflicts of interest. We also include the amount of VC investments and the number of VC rounds. Table 3.1 shows that between 2004 and 2014, our sample companies obtained USD 24.2 bn in 2,563 VC financing rounds. Companies with at least one strategic alliance obtain more VC rounds and higher VC amounts than companies that enter no alliances.

We also control for the size of the VC network since ties between VC firms might affect the exit choice and the likelihood of entering a strategic alliance. We define the network as the ratio of the number of syndication partners to the total number of active VC firms in a particular time period. A VC firm is active if it invested in at least one portfolio company in this period. To construct this measure at the company level, we use the average network of all involved VC firms.

3.4 Methods

3.4.1 Pooled OLS and fixed effect estimations

We construct a panel dataset on an annual basis and first estimate the relationship between strategic alliances and the different types of exits with pooled OLS regressions. We begin by estimating different specifications of the dependent variable *IPO exit*. We exclude all companies that exited through an M&A. We proceed similarly for the dependent variable *M&A exit*.[4]

A problem with pooled OLS models is that they do not account for unobserved heterogeneity across companies that may be related to the likelihood of an IPO or an M&A. For example, high-quality companies may have a higher likelihood of entering a strategic alliance than low-quality companies, but they are also more likely to realize a successful exit. If this is the case, the coefficient on the alliance variable would be biased upwards. Therefore, we include company fixed effects in the next step to account for unobserved time invariant heterogeneity at the company level, such as factors that do not change over time, but that may affect the likelihood of an IPO or an M&A and strategic alliance activity.

3.4.2 Multinomial logit and survival models

Pooled OLS and fixed effect estimations may raise three concerns. First, these models treat the decision to go public and the status of being public as if they were equal because we code the dependent variable as one in the year in which an exit occurred and in all following years. Second, they ignore the time lapse between the strategic alliance formation and the exit event. Third, we treat the IPO and M&A exits independently because, in their respective analyses, we exclude companies that exited through the alternative channel (IPO or M&A).

To account for these concerns, we run several additional analyses. We address the first and second concerns by estimating survival models. We specify an ex-

[4]We use a linear probability model because non-linear models have several disadvantages such as neglected heterogeneity, heteroscedasticity, and non-normality in the latent variable model or a possible incidental parameter problem. Because we are interested in average marginal effects, linear regressions are reasonable in this context (see, e.g., pp. 563, 583, 599-604, 619-625: Wooldridge 2010).

ponential survival distribution and include a frailty parameter in each model. To deal with the third concern, we estimate a multinomial logistic model for the entire panel of firms. In addition, we estimate a competing risk model (Fine and Gray 1999), which addresses all three concerns.

3.4.3 Matching

One caveat in some prior studies is that they treat the formation of a strategic alliance as an exogenous event, though theory may suggest that it is a deliberate strategic choice by the VC firms and a way to bring about their proposed value-added. Since we want to draw causal inferences, we cannot ignore this inherent endogeneity. In contrast to previous empirical studies, we treat the decision for or against a strategic alliance as an endogenous strategic choice. We extend the ideas put forward in Hamilton and Nickerson (2003) by not only accounting for self-selection in strategic choices, but also by modeling the alliance as a treatment effect.

We apply propensity score matching to deal with the potential self-selection. Based on observable characteristics, we match similar companies that have no strategic alliances to companies that have at least one strategic alliance (based on their predicted probability to enter an alliance). We estimate the propensity scores with a logistic regression and employ company and VC characteristics. More specifically, we include the founding year and the number of patents to control for similar company characteristics. Furthermore, we use the logs of the total number of involved VC firms, total VC rounds, and total VC amount to control for investment characteristics. Finally, we employ the average network of the participating VC firms to control for VC firm features. To construct the counterfactual outcome, we employ the kernel matching algorithm with 0.01 bandwidth. Then, we calculate the average treatment effect on the treated (ATT), which is the difference between the treatment and the control group.

Propensity score matching relies on two important assumptions. First, conditional independence (CIA) requires that potential outcomes are independent of treatment assignment given a set of covariates X. Due to the potential for a dimensionality problem, we follow the approach in Rosenbaum and Rubin (1983)

and use propensity scores as balancing scores. The second necessary assumption is the overlap condition or common support, which rules out the phenomenon of perfect predictability of the treatment indicator D given the set of covariates X. We impose common support by dropping the treated observations with propensity scores that are above the maximum, or below the minimum values of the control observations.

The major drawback of propensity score matching is that one can only match on observable characteristics. The exclusion of unobservable characteristics can lead to biases if these characteristics nfluence the observed outcome and the treatment variable simultaneously. We conduct a sensitivity analysis to investigate how much variation in the unobserved variables can exist without impairing the result of the matching approach. We describe the procedure, which follows Rosenbaum (2002), Caliendo and Kopeinig (2008), and Aakvik (2001), in the Appendix.

3.5 Results

3.5.1 Full sample

We start by reporting the results from the pooled OLS and fixed effect models. Panel A of Table 3.2 shows the results from the pooled OLS regressions with IPO exit as the dependent variable. In models (1) to (5), we use different measures to capture the strategic alliance activity. In the first two models, we focus on the alliance activity in the year prior to the exit. Both the number of strategic alliances (1) and the strategic alliance dummy (2) are positively related to IPO exit and the coefficient is statistically highly significant. Strategic alliance activity increases the IPO likelihood in the following year by 8.53 percentage points, and every strategic alliance is associated with a 5.19 percentage point increase in this likelihood. In models (3)-(5), instead of looking only at the year prior to the exit, we consider a five-year horizon. Models (3) and (4) capture the aggregate alliance activity within this horizon, which has a positive effect. Model (5) introduces a separate variable for each lag. We find the strongest effect in the year prior to the IPO. These results confirm the positive association between strategic alliance activity and IPOs.

In all regressions, we account for changes in economic conditions with time fixed effects. As control variables, we employ the number of VC rounds, number of VC firms, number of new investments, VC amount, VC network, and patents granted. The last two variables are based on the prior four years. Since we construct these variables from our database, the inclusion of four lags leads to a large drop in the number of observations. We deal with this issue in specifications (6) and (7), in which we construct our network and patent variable from the previous year's data and re-run models (1) and (2) with these two alternative control variables. Our results for the strategic alliance variables are similar. As to the control variables, we find that better networked VC firms and higher patenting activity are associated with a higher likelihood of IPOs. The definitions of all variables are in Table 3.9.

Panel B depicts the results of the same models with M&A exit as the dependent variable. Models (1) and (2) suggest a negative relationship between strategic alliance activity and M&A exit in the subsequent year. When we consider a five-year horizon in models (3) and (4), the strategic alliance effect becomes insignificant. When we include the variables that count the number of strategic alliances in each year during the five-year horizon in model (5), we find a negative and significant effect in the year preceding the M&A, consistent with the result in model (1). The effect stays negative in the years minus two and minus three, but it lacks significance. The coefficient sign changes in year minus four, in which it turns positive, and it becomes statistically significant in year minus five. These results suggest that the strategic alliance activity close to the M&A event has a negative effect on the M&A exit, while earlier alliance activity (five years prior to the exit) has a positive effect.

When we estimate the same regressions for both types of exits with company fixed effects (see Table 3.3), the strategic alliance effects are approximately 2.3 to 2.5 times smaller for IPO exits (and not much different for M&A exits). Strategic alliance activity increases the IPO likelihood in the following year by 3.3 percentage points, and every strategic alliance is associated with a 2.2 percentage point increase in this likelihood. In addition, we find positive and statistically significant effects in years minus two through minus four. The effect of strategic alliances on M&A activity is again insignificant over the five-year horizon, negative in year minus one, and positive in year minus five. Comparing these results with our find-

ings in Table 3.2 suggests that the unobserved company characteristics associated with a higher likelihood to close a strategic alliance are at the same time positively linked to the likelihood of an IPO exit.

We proceed with the multinomial logit and survival models.[5] The results from the multinomial logistic model with the entire panel of firms show that IPOs are more likely when there are more strategic alliances in the year before the IPO. In addition, strategic alliances in the year before an M&A are negatively related to M&As. The coefficient becomes positive in year minus three and significant at the one percent level in years minus four and minus five.

The results from the survival models are qualitatively similar. We find a positive relationship between the number of strategic alliances in the last five years and an IPO event. Each additional strategic alliance in the last five years increases the probability of an IPO by around 21 percent (p-value: 0.045). When we estimate the models for M&A exit, we do not find that strategic alliance activity has a significant effect. The coefficient of the number of strategic alliances in the past five years is positive, but not significant (p-value: 0.427). Alternatively, we apply a competing-risks analysis, in which we define the time between the treatment and the event of interest as the time between the first strategic alliance and exit (IPO or M&A). When we set the IPO as the event of interest and an M&A as the competing-risk event, the sub-hazard ratio (SHR) of the number of strategic alliances in the last five years is greater than one and statistically significant (p-value: 0.016). Furthermore, when the M&A is the event of interest and the IPO is the competing-risk event, the effect of strategic alliances is statistically insignificant (p-value=0.402) and the SHR is below one.

To summarize, all these results are consistent with the view that strategic alliances certify company quality for potential new buyers at the IPO exit, but not at the M&A exit.

3.5.2 Matching

Panel A of Table 3.4 shows the ATT for companies that exited via an IPO. Companies with at least one strategic alliance have a 7.9 percentage point higher like-

[5] We do not present the results here, but they are available from the authors upon request.

lihood of an IPO than companies without a strategic alliance are in the matched sample. The difference is statistically significant with a t-value equal to 2.16. The ATT is almost two times larger in the unmatched sample (17.5 percentage points), indicating that self-selection accounts for a sizeable part of the total effect. The table further shows that our matching approach was successful in reducing the standardized bias[6] substantially. The balancing was successful because the mean bias was reduced from 37.9% before matching to 2.3% after matching, and the median bias decreased from 45.7% to 2.3%. Moreover, after matching, the difference in the means of all variables between the treated and control groups is below 5%, and is never statistically significant. For four out of the six variables we included in the matching procedure, we were able to reduce the bias by more than 92%. In total, we included 564 companies in the analysis, where 12 untreated and 16 treated companies were outside the common support area and 353 untreated and 183 treated companies were in the support area.

Panel B summarizes the results for companies that exited through M&A. The ATT in the unmatched sample is 3.1 percentage points and after matching, it is down to 1.1 percentage points, both values are statistically insignificant. With matching, the mean bias drops from 35.4% to 3.6% and the median bias decreased from 43.0% to 2.1%. Similar to Panel A, we were able to reduce a substantial part of the bias between the variables. In two out of the six variables, the mean bias is still above 5% (*ln(Total investors)* and *Total patents by appl.*), but below 10%. The difference in means after matching is always statistically insignificant. This part of the analysis included 567 companies; 390 untreated and 177 treated companies were inside the common support area.

Table 3.5 shows the results of the sensitivity check to analyze how much variation in the unobserved variables can exist without impairing the result of the matching approach. The first row reports the different values of the parameter Gamma (Γ). This is equal to the odds of differential assignment due to unobserved factors. The values vary between 1 (the two observations have the same odds of receiving treatment and they do not differ in an unobserved way) and 2.5 (the observations could differ in their odds of receiving treatment by a factor of as much as 2.5). Rows 2–3 report the Mantel-Haenszel statistics under the assump-

[6]We calculate the standardized bias following Rosenbaum and Rubin (1985).

tion that the treatment effect is overestimated (Q^{+}_{MH}) or underestimated (Q^{-}_{MH}). These rows show the results when the bounds of the test statistic move apart, and therefore indicate the sensitivity of the estimated treatment effect to unobserved bias. The last two rows report the significance levels for each test statistic. We can interpret the different bounds for the given values of Γ as follows. If there is a positive unobserved self-selection; that is, when companies that are most likely to enter a strategic alliance also have a higher probability of having a successful exit, then the treatment effect is overestimated and the bounds of the test statistic must be adjusted downwards. If there is negative unobserved self-selection, meaning that the companies that are most likely to enter a strategic alliance have the lowest probability of having a successful exit, then the treatment effect is underestimated and the bounds must be adjusted upwards.

The overall conclusion from Table 3.5 is that the estimated treatment effect is not sensitive to unobserved bias up to a certain level. When Γ increases to 2, the test statistic Q^{+}_{MH} is significant at the 5% level (p-value of 0.025) and for Γ of 2.25, it is still significant at the 10% level (p-value of 0.065). That means that the odds of receiving treatment; that is, entering a strategic alliance, can differ between two companies up to 200% in an unobserved way, and we would still find a positive and significant treatment effect.

3.5.3 Robustness

To account for the potential problems of right censoring, we perform an additional analysis in which we exclude all companies that obtained a VC round in the last two years of our sample period (2013 and 2014) because it is likely that these companies will realize a successful exit in the following years. The analysis confirms our main results; the effects are slightly stronger (see Table 3.6).

Regarding the censoring problem in the propensity score matching, we also apply propensity score matching on the reduced sample, in which we exclude companies that received a VC round in 2013 or 2014. The difference in the unmatched sample for IPO exits is 20.1 percentage points (t-value: 5.80) and for M&A exits, 6.1 percentage points (t-value: 1.27). The ATT is still much lower after matching. The treatment effect on IPOs decreases to 13.8 percentage points (t-value: 2.89)

and to 1.7 percentage points (t-value: 0.29) for M&A exits. The mean bias is 4.8% and 5.6%.[7]

After matching, we can also control for unobserved and observed heterogeneity and censoring. Table 3.7 shows the results for models that correspond to those in Table 3.6, but are based only on the matched sample. Consistent with the prior results, we find positive and statistically significant effects of strategic alliance activity within the five-year horizon preceding the exit for IPOs, but not for M&As. The effect is positive for years minus one through minus three for IPOs, negative for year minus one, and positive for year minus five for M&As. The statistical and economic significance of the strategic alliance variables are smaller, indicating, again, that self-selection is a relevant issue.

We also test alternative matching approaches to ensure that our results are not driven by the choice of matching algorithm. More specifically, we apply 1, 2, 5, and 10-nearest neighbors matching, radius matching with different specified radii, trimming, and kernel matching with different bandwidths. The estimates of the ATT do not differ much (see Table 3.8). In particular, the treatment effect for IPOs varies between 6.8% and 10.7%. The treatment effect for M&As remains insignificant within the matched sample and ranges between -2.4% and 2.8%. We estimate multivariate regressions from Table 3.7 with these different samples, and the main conclusions remain the same.

3.6 Discussion and conclusion

Our results consistently show that strategic alliances have different effects on different exit channels. We demonstrate that strategic alliances are associated with a high likelihood of an IPO. Furthermore, our findings indicate that M&As are not favored when firms make recent alliances. On the contrary, the first three lags of the number of strategic alliances have a negative effect on the M&A likelihood, though only the first lag is significant. The strategic alliance effect becomes positive starting with the fourth lag, and turns statistically significant with the fifth lag, suggesting that strategic alliances increase the likelihood of M&As when the

[7] We do not present the results here, but they are available from the authors upon request.

company had no opportunity to go public. This conclusion is supported when we look at the average time to exit, which is significantly shorter for IPOs than for M&As.

In light of the agency problems that occur when VC firms and other incumbents aim to exit their financed ventures, strategic alliances may provide valuable information for potential buyers in an IPO process. Plummer et al. (2016) show that third-party affiliations are helpful for ventures when seeking external capital because these affiliations certify the quality of the new venture. Strategic alliances seem to work in a similar way. They certify good quality and promote quicker paths to IPOs. On the other hand, such alliances do not lead to quicker M&As because before an M&A, an interested buyer performs due diligence and a certification device may not provide much additional information in the course of an M&A.

These results have implications not only for academic research, but also for entrepreneurs and VC firms, which should be aware of the implications of strategic alliances. According to Giot and Schwienbacher (2007) and Black and Gilson (1998), IPOs are the preferred exit choice for VC firms. Therefore, VC firms might increase their chances of taking their companies public with their portfolio company by promoting and encouraging strategic alliances.

The effects we find are lower than those reported in prior studies such as those by Ozmel et al. (2013b) or Qi et al. (2015). The comparison of the results of our various analyses shows that the results might be heavily biased without endogeneity corrections, particularly if we do not account for self-selection into the strategic alliance activity and unobserved heterogeneity. In the unmatched sample, we find that companies that entered at least one strategic alliance have a 17.5 percentage point higher likelihood of an IPO than their peers without any strategic alliance activity. Exit through M&As is 3.1 percentage points more likely (but not statistically significant) if companies engaged in strategic alliances in the past. However, after controlling for observed and unobserved heterogeneity, self-selection, and censoring, we conclude that the effect of strategic alliances is less than what a simple comparison revealed. Companies that entered at least one strategic alliance in the five-year period prior to exit realized a 9.8 percentage point higher likelihood of an IPO, while the aggregate effect (over 5 years) on M&As remains insignificant.

Our study is not without limitations. Although we can eliminate a number of endogeneity issues, there is still a potential risk from unobserved characteristics that vary over time, such as management performance or the ability of the entrepreneurs and company owners. In addition, we cannot observe the true motivation of entrepreneurs when they choose to enter a strategic alliance. This can lead to biased results in the propensity score matching, in which we match treated and untreated companies based on observed characteristics. For this issue, a survey study could shed more light on what drives young companies to enter a strategic alliance. For example, researchers could analyze the role of VC firm networks and connections to prior syndication partners in promoting strategic alliances.

Furthermore, we did not uncover the role of strategic alliances in the M&A process. We showed that recent strategic alliances are negatively related to M&As; however, there might be other reasons that companies enter strategic alliances, such as an expansion to international markets. Further research should concentrate on the reasons behind the choice between strategic alliances and M&As. It is important to understand the point of time at which the companies choose strategic alliances rather than M&As. In this context, it is not clear how the VC is involved in this decision.

Appendix 3.A: Tables

Table 3.1. Summary statistics

Strategic alliances	Companies	IPOs	t(diff)	M&As	t(diff)	Patent applications	t(diff)	Patent grants	t(diff)	VC rounds	t(diff)	VC amount (USD mn)	t(diff)
578	663	78		99		4,531		3,342		2,563		24,226	
		total						mean					
0	429 (64.71%)	28 (6.53%)	-5.80	64 (14.92%)	-0.01	4.65	-5.96	3.44	-5.21	3.38	-6.54	26.12	-7.84
at least 1	234 (35.29%)	50 (21.37%)		35 (14.96%)		10.84		7.97		4.76		55.65	
1	102	15 (14.71%)		16 (15.69%)		7.85		6.09		4.36		40.91	
2	58	9 (15.52%)		11 (18.97%)		8.76		6.29		4.81		48.38	
3	32	10 (31.25%)		4 (12.50%)		11.94		8.19		5.59		74.77	
4	11	4 (36.36%)		1 (9.09%)		13.09		11.36		4.91		66.89	
5	12	5 (41.67%)		3 (25.00%)		7.08		3.50		5.00		94.88	
6	6	1 (16.67%)		0		42.00		33.67		3.00		39.92	
7	4	2 (50.00%)		0		16.25		10.25		6.75		103.31	
8	1	1 (100.00%)		0		40.00		21.00		5.00		47.17	
9	4	3 (75.00%)		0		35.00		24.50		6.50		139.98	
12	1	0		0		74.00		51.00		6.00		331.64	
13	2	0		0		3.50		1.50		5.50		51.09	
14	1	0		0		39.00		34.00		5.00		83.80	

Table 3.2. Pooled OLS estimates

Panel A: IPO exit

	Dependent variable: IPO exit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. of alliances	0.0519***				0.0446*	0.0488***	
$(t-1)$	(0.0174)				(0.0232)	(0.0161)	
Alliance dummy		0.0853***					0.0799***
$(t-1)$		(0.0229)					(0.0217)
No. of alliances			0.0260***				
$(t-1/t-5)$			(0.0079)				
Alliance dummy				0.0859***			
$(t-1/t-5)$				(0.0175)			
No. of alliances					0.0148		
$(t-2)$					(0.0213)		
No. of alliances					0.0084		
$(t-3)$					(0.0182)		
No. of alliances					0.0318		
$(t-4)$					(0.0257)		
No. of alliances					0.0377		
$(t-5)$					(0.0369)		
Patents granted	0.0031**	0.0030**	0.0022*	0.0021	0.0023*		
$(t-1/t-4)$	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)		
Patents granted						0.0066	0.0063
$(t-1)$						(0.0041)	(0.0041)
VC network	0.9598***	0.9593***	1.6563***	1.6275***	1.6389***		
$(t-1/t-4)$	(0.1875)	(0.1868)	(0.2823)	(0.2804)	(0.2817)		
VC network						0.9581***	0.9590***
$(t-1)$						(0.1893)	(0.1887)
VC rounds	-0.0116	-0.0112	-0.0191	-0.0170	-0.0190	-0.0128	-0.0125
$(t-1)$	(0.0093)	(0.0094)	(0.0143)	(0.0143)	(0.0144)	(0.0090)	(0.0090)
VC investors	0.0020	0.0016	0.0060	0.0043	0.0060	0.0019	0.0015
$(t-1)$	(0.0049)	(0.0049)	(0.0077)	(0.0078)	(0.0077)	(0.0046)	(0.0046)
VC new	-0.0097**	-0.0093*	-0.0139	-0.0126	-0.0141	-0.0106**	-0.0102**
$(t-1)$	(0.0048)	(0.0048)	(0.0102)	(0.0102)	(0.0102)	(0.0041)	(0.0041)
VC amount	0.0035***	0.0035***	0.0044**	0.0045**	0.0044**	0.0036***	0.0036***
$(t-1)$	(0.0013)	(0.0013)	(0.0020)	(0.0020)	(0.0020)	(0.0012)	(0.0012)
Constant	-0.0338**	-0.0341**	-0.0602**	-0.0652**	-0.0615**	-0.0176	-0.0175
	(0.0142)	(0.0141)	(0.0307)	(0.0307)	(0.0308)	(0.0170)	(0.0170)
Company FE	No	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,734	2,734	1,791	1,791	1,791	3,270	3,270
F	10.619	11.091	9.927	10.941	7.481	9.370	9.628

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2. *continued*

Panel B: M&A exit

	Dependent variable: M&A exit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. of alliances	-0.0442***				-0.0474***	-0.0441***	
$(t-1)$	(0.0077)				(0.0118)	(0.0087)	
Alliance dummy		-0.0674***					-0.0720***
$(t-1)$		(0.0153)					(0.0155)
No. of alliances			-0.0029				
$(t-1/t-5)$			(0.0063)				
Alliance dummy				0.0239			
$(t-1/t-5)$				(0.0188)			
No. of alliances					-0.0203		
$(t-2)$					(0.0177)		
No. of alliances					-0.0083		
$(t-3)$					(0.0192)		
No. of alliances					0.0388		
$(t-4)$					(0.0266)		
No. of alliances					0.0709**		
$(t-5)$					(0.0349)		
Patents granted	0.0092***	0.0091***	0.0084***	0.0077***	0.0077***		
$(t-1/t-4)$	(0.0023)	(0.0023)	(0.0025)	(0.0025)	(0.0025)		
Patents granted						0.0101*	0.0101**
$(t-1)$						(0.0052)	(0.0052)
VC network	0.7790***	0.7809***	1.2300***	1.2181***	1.2515***		
$(t-1/t-4)$	(0.2078)	(0.2078)	(0.2910)	(0.2899)	(0.2900)		
VC network						0.9493***	0.9525***
$(t-1)$						(0.2299)	(0.2298)
VC rounds	-0.0584***	-0.0583***	-0.0776***	-0.0755***	-0.0807***	-0.0763***	-0.0761***
$(t-1)$	(0.0087)	(0.0087)	(0.0126)	(0.0126)	(0.0126)	(0.0088)	(0.0088)
VC investors	0.0026	0.0027	0.0051	0.0039	0.0059	0.0028	0.0029
$(t-1)$	(0.0035)	(0.0035)	(0.0065)	(0.0065)	(0.0064)	(0.0034)	(0.0034)
VC new	-0.0045	-0.0044	-0.0079	-0.0071	-0.0076	-0.0064	-0.0064
$(t-1)$	(0.0038)	(0.0038)	(0.0065)	(0.0066)	(0.0065)	(0.0041)	(0.0041)
VC amount	0.0002	0.0002	-0.0001	-0.0001	0.0001	0.0007	0.0007
$(t-1)$	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Constant	0.0592***	0.0594***	0.0216	0.0176	0.0348	0.0993**	0.0987**
	(0.0149)	(0.0149)	(0.0248)	(0.0252)	(0.0253)	(0.0468)	(0.0469)
Company FE	No	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,830	2,830	1,841	1,841	1,841	3,433	3,433
F	13.912	13.652	9.910	9.978	8.367	15.786	15.721

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3. Fixed effects estimates

Panel A: IPO exit

	Dependent variable: IPO exit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. of alliances	0.0223**				0.0356***	0.0283**	
$(t-1)$	(0.0109)				(0.0127)	(0.0129)	
Alliance dummy		0.0335**					0.0368*
$(t-1)$		(0.0165)					(0.0192)
No. of alliances			0.0296**				
$(t-1/t-5)$			(0.0118)				
Alliance dummy				0.0640**			
$(t-1/t-5)$				(0.0265)			
No. of alliances					0.0237*		
$(t-2)$					(0.0143)		
No. of alliances					0.0332**		
$(t-3)$					(0.0146)		
No. of alliances					0.0375*		
$(t-4)$					(0.0192)		
No. of alliances					0.0123		
$(t-5)$					(0.0200)		
Patents granted	0.0036*	0.0036*	0.0027	0.0028	0.0028		
$(t-1/t-4)$	(0.0020)	(0.0020)	(0.0025)	(0.0027)	(0.0026)		
Patents granted						0.0041	0.0040
$(t-1)$						(0.0048)	(0.0049)
VC network	-0.3778	-0.3776	-1.2891	-1.2773	-1.3300		
$(t-1/t-4)$	(0.6495)	(0.6495)	(1.2640)	(1.2626)	(1.2594)		
VC network						0.4624	0.4765
$(t-1)$						(0.5960)	(0.6006)
VC rounds	0.0264***	0.0265***	0.0306**	0.0321**	0.0308**	0.0224**	0.0224**
$(t-1)$	(0.0101)	(0.0101)	(0.0141)	(0.0141)	(0.0139)	(0.0093)	(0.0093)
VC investors	-0.0048	-0.0049	-0.0088	-0.0095	-0.0089	-0.0034	-0.0035
$(t-1)$	(0.0044)	(0.0044)	(0.0070)	(0.0069)	(0.0069)	(0.0037)	(0.0037)
VC new	-0.0030	-0.0029	-0.0101	-0.0088	-0.0096	-0.0061*	-0.0061*
$(t-1)$	(0.0043)	(0.0043)	(0.0098)	(0.0098)	(0.0099)	(0.0035)	(0.0035)
VC amount	0.0006	0.0006	0.0012	0.0011	0.0012	0.0008	0.0008
$(t-1)$	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0005)	(0.0005)
Constant	-0.0173	-0.0175	0.0022	0.0014	0.0018	-0.1127*	-0.1133*
	(0.0277)	(0.0277)	(0.0518)	(0.0521)	(0.0518)	(0.0669)	(0.0672)
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,734	2,734	1,791	1,791	1,791	3,270	3,270
F	5.821	5.834	5.161	5.082	3.987	5.135	5.115

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3. *continued*

Panel B: M&A exit

	Dependent variable: M&A exit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. of alliances	-0.0422***				-0.0333*	-0.0392***	
$(t-1)$	(0.0124)				(0.0175)	(0.0111)	
Alliance dummy		-0.0599***					-0.0599***
$(t-1)$		(0.0169)					(0.0168)
No. of alliances			-0.0128				
$(t-1/t-5)$			(0.0139)				
Alliance dummy				0.0158			
$(t-1/t-5)$				(0.0369)			
No. of alliances					-0.0153		
$(t-2)$					(0.0208)		
No. of alliances					-0.0254		
$(t-3)$					(0.0246)		
No. of alliances					0.0027		
$(t-4)$					(0.0195)		
No. of alliances					0.0419**		
$(t-5)$					(0.0194)		
Patents granted	0.0103**	0.0101**	0.0083**	0.0079**	0.0076**		
$(t-1/t-4)$	(0.0040)	(0.0040)	(0.0037)	(0.0037)	(0.0038)		
Patents granted						0.0087*	0.0088*
$(t-1)$						(0.0050)	(0.0050)
VC network	-0.4312	-0.4532	1.4232	1.3560	1.4695		
$(t-1/t-4)$	(0.6949)	(0.6940)	(1.2626)	(1.2668)	(1.2390)		
VC network						0.4750	0.4591
$(t-1)$						(0.6432)	(0.6417)
VC rounds	0.0009	0.0013	-0.0021	-0.0019	-0.0048	-0.0051	-0.0047
$(t-1)$	(0.0093)	(0.0094)	(0.0106)	(0.0106)	(0.0106)	(0.0094)	(0.0093)
VC investors	0.0039	0.0037	0.0019	0.0016	0.0024	0.0027	0.0026
$(t-1)$	(0.0035)	(0.0035)	(0.0041)	(0.0041)	(0.0041)	(0.0036)	(0.0036)
VC new	-0.0024	-0.0022	-0.0038	-0.0034	-0.0049	-0.0023	-0.0022
$(t-1)$	(0.0048)	(0.0048)	(0.0053)	(0.0055)	(0.0053)	(0.0046)	(0.0046)
VC amount	-0.0014*	-0.0014*	-0.0004	-0.0004	-0.0005	-0.0019**	-0.0019**
$(t-1)$	(0.0008)	(0.0008)	(0.0005)	(0.0005)	(0.0005)	(0.0008)	(0.0008)
Constant	-0.0103	-0.0094	-0.0801	-0.0810	-0.0686	-0.0803	-0.0807
	(0.0283)	(0.0282)	(0.0597)	(0.0603)	(0.0578)	(0.0700)	(0.0700)
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,830	2,830	1,841	1,841	1,841	3,433	3,433
F	6.704	6.697	3.722	3.662	2.887	6.613	6.624

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4. Propensity score matching: Results and balancing

Panel A: IPO exit

Results:	Sample	Treated	Control	Diff.	S.E.	t	MeanBias	MedBias
IPO exit	Unmatched	0.251	0.077	0.175	0.030	5.90	37.9	45.7
	Matched	0.224	0.145	0.079	0.037	2.16	2.3	2.3

Balancing:	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct. |bias|	t	t-test p> |t|	Var(T)/ Var(C)
Foundation year	U	2006.1	2006.2	-7.5		-0.85	0.395	1.05
	M	2006.2	2006.1	1.8	75.6	0.17	0.864	0.97
ln(Total VC rounds)	U	1.4129	1.0481	47.5		5.38	0.000	0.99
	M	1.3819	1.3629	2.5	94.8	0.24	0.808	1.15
ln(Total VC amount)	U	3.2571	2.0783	66.8		7.48	0.000	0.82
	M	3.1433	3.0995	2.5	96.3	0.26	0.799	1.12
ln(Total investors)	U	1.4162	1.0565	52.3		5.97	0.000	1.08
	M	1.3640	1.3535	1.5	97.1	0.15	0.880	1.18
Total patents by appl.	U	11.603	4.7288	44.0		5.74	0.000	10.52∗
	M	7.1366	7.6596	-3.3	92.4	-0.68	0.496	0.98
VC network (mean)	U	0.0326	0.0299	9.5		1.06	0.291	0.77
	M	0.0323	0.0329	-2.1	77.9	-0.21	0.836	0.93

∗ if variance ratio outside [0.76; 1.32] for U and [0.75; 1.34] for M

Panel B: M&A exit

Results:	Sample	Treated	Control	Diff.	S.E.	t	MeanBias	MedBias
M&A exit	Unmatched	0.190	0.160	0.031	0.033	0.92	35.4	43.0
	Matched	0.192	0.181	0.011	0.040	0.29	3.6	2.1

Balancing:	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct. |bias|	t	t-test p> |t|	Var(T)/ Var(C)
Foundation year	U	2006.1	2006.2	-10.8		-1.22	0.224	1.05
	M	2006.1	2006.1	-1.6	85.4	-0.15	0.881	1.13
ln(Total VC rounds)	U	1.3262	0.9926	45.3		5.05	0.000	0.91
	M	1.3152	1.3220	-0.9	98.0	-0.09	0.931	0.89
ln(Total VC amount)	U	3.0373	2.0498	59.2		6.49	0.000	0.77
	M	2.9803	2.9362	2.6	95.5	0.27	0.790	0.97
ln(Total investors)	U	1.3517	1.0273	49.3		5.54	0.000	1.01
	M	1.3342	1.2843	7.6	84.6	0.73	0.463	1.15
Total patents by appl.	U	8.2174	4.5137	40.7		5.12	0.000	3.43∗
	M	6.5593	7.2322	-7.4	81.8	-0.88	0.382	0.87
VC network (mean)	U	0.0312	0.0293	7.3		0.79	0.428	0.70∗
	M	0.0314	0.0310	1.4	81.0	0.14	0.892	0.86

∗ if variance ratio outside [0.75; 1.34] for U and [0.74; 1.35] for M

Table 3.5. Propensity score matching: Sensitivity analysis

Gamma	1	1.25	1.5	1.75	2	2.25	2.5
Q^{+}_{MH}	4.7259	3.8091	3.0805	2.4778	1.9634	1.5144	1.1155
Q^{-}_{MH}	4.7259	5.6929	6.5177	7.2470	7.9061	8.5112	9.0731
p^{+}_{MH}	1.10E-06	0.0000	0.0010	0.0066	0.0248	0.0650	0.1323
p^{-}_{MH}	1.10E-06	6.20E-09	3.60E-11	2.10E-13	1.30E-15	0	0

Gamma: odds of differential assignment due to unobserved factors
Q^{+}_{MH}: Mantel-Haenszel statistic (assumption: overestimation of treatment effect)
Q^{-}_{MH}: Mantel-Haenszel statistic (assumption: underestimation of treatment effect)
p^{+}_{MH}: significance level (assumption: overestimation of treatment effect)
p^{-}_{MH}: significance level (assumption: underestimation of treatment effect)

Table 3.6. Fixed effects estimates, excl. companies with recent VC investments

Panel A: IPO exit

	Dependent variable: IPO exit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. of alliances	0.0346*				0.0405**	0.0475**	
$(t-1)$	(0.0182)				(0.0189)	(0.0208)	
Alliance dummy		0.0500**					0.0595**
$(t-1)$		(0.0235)					(0.0285)
No. of alliances			0.0392***				
$(t-1/t-5)$			(0.0140)				
Alliance dummy				0.1075***			
$(t-1/t-5)$				(0.0354)			
No. of alliances					0.0418**		
$(t-2)$					(0.0202)		
No. of alliances					0.0459**		
$(t-3)$					(0.0219)		
No. of alliances					0.0313*		
$(t-4)$					(0.0180)		
No. of alliances					0.0249		
$(t-5)$					(0.0215)		
Patents granted	0.0056*	0.0055*	0.0042	0.0045	0.0043		
$(t-1/t-4)$	(0.0032)	(0.0033)	(0.0033)	(0.0033)	(0.0033)		
Patents granted						0.0116*	0.0118*
$(t-1)$						(0.0068)	(0.0069)
VC network	-0.1775	-0.1646	-3.1109	-2.7553	-3.0855		
$(t-1/t-4)$	(0.9245)	(0.9299)	(2.6380)	(2.6073)	(2.6305)		
VC network						0.7685	0.8061
$(t-1)$						(0.9172)	(0.9364)
VC rounds	0.0255**	0.0257**	0.0367*	0.0393*	0.0378*	0.0237**	0.0239**
$(t-1)$	(0.0116)	(0.0116)	(0.0201)	(0.0200)	(0.0194)	(0.0101)	(0.0101)
VC investors	-0.0051	-0.0053	-0.0062	-0.0077	-0.0069	-0.0029	-0.0031
$(t-1)$	(0.0055)	(0.0055)	(0.0099)	(0.0099)	(0.0095)	(0.0044)	(0.0044)
VC new	-0.0062	-0.0059	-0.0280*	-0.0250	-0.0268	-0.0074*	-0.0073*
$(t-1)$	(0.0057)	(0.0056)	(0.0161)	(0.0165)	(0.0164)	(0.0043)	(0.0043)
VC amount	-0.0005	-0.0005	0.0001	-0.0000	0.0001	-0.0001	-0.0001
$(t-1)$	(0.0006)	(0.0006)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Constant	0.0032	0.0028	0.0884	0.0758	0.0864	-0.0984	-0.1000
	(0.0395)	(0.0396)	(0.0730)	(0.0737)	(0.0728)	(0.0812)	(0.0821)
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,711	1,711	1,105	1,105	1,105	2,112	2,112
F	2.863	2.882	2.522	2.221	2.002	2.717	2.683

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6. *continued*

Panel B: M&A exit

	Dependent variable: M&A exit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. of alliances	-0.0663***				-0.0593**	-0.0588***	
$(t-1)$	(0.0167)				(0.0251)	(0.0159)	
Alliance dummy		-0.0825***					-0.0779***
$(t-1)$		(0.0253)					(0.0244)
No. of alliances			-0.0172				
$(t-1/t-5)$			(0.0153)				
Alliance dummy				0.0317			
$(t-1/t-5)$				(0.0477)			
No. of alliances					-0.0208		
$(t-2)$					(0.0231)		
No. of alliances					-0.0344		
$(t-3)$					(0.0357)		
No. of alliances					0.0167		
$(t-4)$					(0.0235)		
No. of alliances					0.0580***		
$(t-5)$					(0.0217)		
Patents granted	0.0200***	0.0199***	0.0153***	0.0150***	0.0151***		
$(t-1/t-4)$	(0.0049)	(0.0049)	(0.0046)	(0.0047)	(0.0045)		
Patents granted						0.0207***	0.0204***
$(t-1)$						(0.0065)	(0.0065)
VC network	-1.0720	-1.1120	0.9858	0.8679	0.9241		
$(t-1/t-4)$	(1.0867)	(1.0850)	(2.8425)	(2.8391)	(2.6288)		
VC network						0.4863	0.4601
$(t-1)$						(0.9516)	(0.9500)
VC rounds	0.0289*	0.0296**	0.0310	0.0292	0.0265	0.0092	0.0101
$(t-1)$	(0.0148)	(0.0150)	(0.0198)	(0.0195)	(0.0198)	(0.0149)	(0.0148)
VC investors	0.0032	0.0027	-0.0037	-0.0027	-0.0022	0.0034	0.0030
$(t-1)$	(0.0054)	(0.0055)	(0.0069)	(0.0067)	(0.0070)	(0.0059)	(0.0059)
VC new	-0.0125	-0.0118	-0.0206	-0.0205	-0.0248*	-0.0086	-0.0083
$(t-1)$	(0.0085)	(0.0086)	(0.0139)	(0.0141)	(0.0142)	(0.0075)	(0.0075)
VC amount	-0.0016	-0.0015	-0.0002	-0.0002	-0.0003	-0.0022**	-0.0022**
$(t-1)$	(0.0010)	(0.0010)	(0.0004)	(0.0004)	(0.0005)	(0.0011)	(0.0010)
Constant	0.0050	0.0059	-0.0629	-0.0665	-0.0364	-0.0452	-0.0458
	(0.0428)	(0.0425)	(0.1002)	(0.1014)	(0.0941)	(0.0810)	(0.0808)
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,936	1,936	1,231	1,231	1,231	2,429	2,429
F	6.677	6.531	3.151	3.070	2.942	6.232	6.228

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7. Fixed effects estimates, excl. companies with recent VC investments, matched sample

Panel A: IPO exit

	Dependent variable: IPO exit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. of alliances	0.0192				0.0276*	0.0324*	
$(t-1)$	(0.0143)				(0.0163)	(0.0195)	
Alliance dummy		0.0371*					0.0439
$(t-1)$		(0.0220)					(0.0284)
No. of alliances			0.0273**				
$(t-1/t-5)$			(0.0118)				
Alliance dummy				0.0982***			
$(t-1/t-5)$				(0.0333)			
No. of alliances					0.0329*		
$(t-2)$					(0.0184)		
No. of alliances					0.0386**		
$(t-3)$					(0.0189)		
No. of alliances					0.0172		
$(t-4)$					(0.0148)		
No. of alliances					0.0084		
$(t-5)$					(0.0121)		
Patents granted	0.0041	0.0043	0.0043	0.0043	0.0042		
$(t-1/t-4)$	(0.0034)	(0.0034)	(0.0041)	(0.0039)	(0.0040)		
Patents granted						0.0034	0.0035
$(t-1)$						(0.0049)	(0.0049)
VC network	-0.1533	-0.1437	-2.4690	-2.1207	-2.4091		
$(t-1/t-4)$	(0.9286)	(0.9356)	(2.9289)	(2.8549)	(2.9210)		
VC network						1.2379	1.2704
$(t-1)$						(0.9293)	(0.9463)
VC rounds	0.0224**	0.0225**	0.0174	0.0179	0.0182	0.0210**	0.0213**
$(t-1)$	(0.0086)	(0.0087)	(0.0160)	(0.0157)	(0.0159)	(0.0089)	(0.0089)
VC investors	-0.0057	-0.0057	0.0026	0.0028	0.0022	-0.0027	-0.0028
$(t-1)$	(0.0051)	(0.0051)	(0.0083)	(0.0082)	(0.0084)	(0.0045)	(0.0045)
VC new	-0.0036	-0.0034	-0.0346**	-0.0326*	-0.0333*	-0.0058	-0.0057
$(t-1)$	(0.0059)	(0.0059)	(0.0170)	(0.0170)	(0.0171)	(0.0046)	(0.0046)
VC amount	-0.0007	-0.0008	-0.0001	-0.0001	-0.0001	-0.0003	-0.0003
$(t-1)$	(0.0006)	(0.0006)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Constant	0.0110	0.0098	0.0636	0.0479	0.0605	-0.0829	-0.0845
	(0.0392)	(0.0393)	(0.0834)	(0.0827)	(0.0832)	(0.0828)	(0.0837)
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,627	1,627	1,045	1,045	1,045	1,998	1,998
F	2.105	2.094	1.986	1.701	1.582	1.974	1.953

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7. *continued*

Panel B: M&A exit

	Dependent variable: M&A exit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. of alliances	-0.0677***				-0.0597**	-0.0581***	
$(t-1)$	(0.0168)				(0.0254)	(0.0160)	
Alliance dummy		-0.0857***					-0.0769***
$(t-1)$		(0.0258)					(0.0248)
No. of alliances			-0.0167				
$(t-1/t-5)$			(0.0155)				
Alliance dummy				0.0344			
$(t-1/t-5)$				(0.0493)			
No. of alliances					-0.0178		
$(t-2)$					(0.0232)		
No. of alliances					-0.0360		
$(t-3)$					(0.0359)		
No. of alliances					0.0166		
$(t-4)$					(0.0238)		
No. of alliances					0.0589***		
$(t-5)$					(0.0221)		
Patents granted	0.0216***	0.0215***	0.0139**	0.0134**	0.0142**		
$(t-1/t-4)$	(0.0061)	(0.0061)	(0.0056)	(0.0056)	(0.0056)		
Patents granted						0.0191***	0.0188**
$(t-1)$						(0.0073)	(0.0073)
VC network	-1.0669	-1.1079	0.9186	0.7989	0.8850		
$(t-1/t-4)$	(1.0851)	(1.0833)	(2.8515)	(2.8472)	(2.6418)		
VC network						0.4690	0.4431
$(t-1)$						(0.9520)	(0.9504)
VC rounds	0.0287*	0.0295*	0.0306	0.0285	0.0263	0.0090	0.0099
$(t-1)$	(0.0150)	(0.0151)	(0.0200)	(0.0197)	(0.0200)	(0.0150)	(0.0149)
VC investors	0.0038	0.0033	-0.0034	-0.0023	-0.0020	0.0040	0.0036
$(t-1)$	(0.0055)	(0.0055)	(0.0069)	(0.0066)	(0.0070)	(0.0059)	(0.0059)
VC new	-0.0137	-0.0131	-0.0212	-0.0211	-0.0254*	-0.0095	-0.0092
$(t-1)$	(0.0086)	(0.0086)	(0.0139)	(0.0141)	(0.0141)	(0.0076)	(0.0076)
VC amount	-0.0016	-0.0015	-0.0002	-0.0002	-0.0003	-0.0022**	-0.0022**
$(t-1)$	(0.0010)	(0.0010)	(0.0004)	(0.0004)	(0.0005)	(0.0011)	(0.0010)
Constant	0.0099	0.0109	-0.0571	-0.0608	-0.0314	-0.0464	-0.0471
	(0.0435)	(0.0433)	(0.1013)	(0.1024)	(0.0952)	(0.0840)	(0.0839)
Company FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,877	1,877	1,198	1,198	1,198	2,358	2,358
F	6.370	6.208	2.828	2.754	2.636	6.067	6.047

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8. Propensity score matching: Robustness of ATT

		Mean					Bias	
	Matching algorithm	Treated	Controls	Difference	S.E.	t	Mean	Median
IPO exit	**Baseline: Kernel (0.01)**	**0.224**	**0.145**	**0.079**	**0.037**	**2.16**	**2.3**	**2.3**
	Kernel (0.05)	0.241	0.151	0.089	0.036	2.49	2.4	2.4
	Kernel (0.1)	0.241	0.148	0.093	0.036	2.60	2.9	2.9
	1-nearest neighbor	0.241	0.141	0.099	0.046	2.17	5.8	5.3
	2-nearest neighbors	0.241	0.144	0.097	0.042	2.31	5.2	4.6
	5-nearest neighbors	0.241	0.156	0.085	0.038	2.25	3.0	2.4
	10-nearest neighbors	0.241	0.152	0.088	0.037	2.41	1.6	1.8
	Caliper (0.1)	0.241	0.141	0.099	0.046	2.17	5.8	5.3
	Caliper (0.05)	0.241	0.141	0.099	0.046	2.17	5.8	5.3
	Caliper (0.01)	0.224	0.142	0.082	0.046	1.78	4.7	3.9
	Caliper (0.001)	0.175	0.100	0.075	0.048	1.57	7.3	6.0
	Trimming (10)	0.206	0.128	0.078	0.047	1.67	5.0	4.0
	Trimming (5)	0.237	0.168	0.068	0.047	1.44	2.2	1.3
	Trimming (1)	0.245	0.138	0.107	0.048	2.24	7.4	6.7
M&A exit	**Baseline: Kernel (0.01)**	**0.192**	**0.181**	**0.011**	**0.040**	**0.29**	**3.6**	**2.1**
	Kernel (0.05)	0.190	0.166	0.024	0.037	0.65	2.6	2.0
	Kernel (0.1)	0.193	0.169	0.024	0.037	0.65	2.9	2.1
	1-nearest neighbor	0.193	0.199	-0.006	0.050	-0.11	5.6	5.7
	2-nearest neighbors	0.193	0.166	0.028	0.043	0.64	5.9	5.0
	5-nearest neighbors	0.193	0.177	0.017	0.040	0.41	1.7	1.9
	10-nearest neighbors	0.193	0.172	0.021	0.039	0.54	2.0	1.9
	Caliper (0.1)	0.193	0.199	-0.006	0.050	-0.11	5.6	5.7
	Caliper (0.05)	0.190	0.201	-0.011	0.050	-0.22	5.5	6.1
	Caliper (0.01)	0.192	0.203	-0.011	0.050	-0.22	5.4	6.2
	Caliper (0.001)	0.219	0.203	0.016	0.055	0.28	6.6	8.1
	Trimming (10)	0.192	0.217	-0.024	0.053	-0.45	6.5	6.0
	Trimming (5)	0.194	0.206	-0.011	0.052	-0.22	5.3	5.9
	Trimming (1)	0.191	0.197	-0.005	0.051	-0.11	5.4	6.3

Appendix 3.B: Matching and unobserved bias

The probability that company i receives treatment, conditional on the explanatory variables x_i, is given by $P(x_i) = P(D = 1|x_i) = G(\beta x_i + \gamma u_i)$. $G(.)$ is the logistic distribution, x_i are the observed variables, u_i is the unobserved variable of observation i, and γ is the effect of the unobserved variable on the probability of receiving treatment. If no unobserved bias exists, then γ equals zero. If γ is not zero, then an unobserved bias exists, and two companies that are similar in the observed variables x_i will differ in the probability of receiving treatment. The odds ratio of two companies i and j that they will receive treatment is

$$\frac{\frac{P(x_i)}{1-P(x_i)}}{\frac{P(x_j}{1-P(x_j)}} = \frac{P(x_i)(1-P(x_j)}{P(x_j)(1-P(x_i))} = \frac{exp(\beta x_j + \gamma u_j)}{exp(\beta x_i + \gamma u_i)} = exp[\gamma(u_i - u_j)]. \tag{3.1}$$

The odds ratio equals one if no difference in unobserved bias exists; that is, when the difference $(u_i - u_j)$ is zero, or when the unobserved variables have no influence on the probability of receiving treatment; that is, when γ equals zero. In all other cases, an unobserved bias exists and two companies that have the same observed covariates will still differ in the probability of receiving treatment. We assume that the unobserved variable is a dummy variable[8] $u_i \in [0, 1]$ and Equation 3.1 imply the following "Rosenbaum-bounds" on the odds ratio that one of the two companies receives treatment:

$$\frac{1}{e^\gamma} \leq \frac{P(x_i)(1-P(x_j))}{P(x_j)(1-P(x_i)} \leq e^\gamma. \tag{3.2}$$

If $\Gamma = e^\gamma$ equals 1, then there is no unobserved bias and both companies have the same probability of receiving treatment. Therefore, Γ is a measure of the degree of allowed difference in the unobserved variables that influence the probability of treatment compared to the case with no unobserved bias. For example, if Γ is equal to 1.5, then the two companies that are similar according to the observed variables could actually differ up to 50% in an unobserved way.

To evaluate the influence of the unobserved bias, we use the non-parametric

[8] A classic example for such an unobserved bias would be motivation. In that case, the dummy variable equals one if the founder of the company is motivated and zero otherwise.

Mantel-Haenszel test statistic (Mantel and Haenszel 1959) given by

$$Q_{MH} = \frac{[\sum_{s=1}^{S}(Y_{1s} - \frac{N_{1s}Y_s}{Ns})]^2}{\sum_{s=1}^{S}\frac{N_{1s}N_{0s}Y_s(N_s-Y_s)}{N_s^2(N_s-1)}}, \tag{3.3}$$

where N_{1s} and N_{0s} are the numbers of treated and untreated individuals, respectively, in stratum s with $N_s = N_{0s} + N_{1s}$. Y_{1s} is the number of successful participants, Y_{0s} is the number of successful non-participants, and Y_s is the number of total successes in stratum s. This test statistic follows a χ^2 distribution with one degree of freedom, and Rosenbaum (2002) shows that for a fixed value of $\Gamma > 1$ and when u_i is a 0/1 dummy variable, Q_{MH} is bounded by two known distributions. When Γ increases, the bounds move apart, and hence reflect uncertainty about the test statistic. Furthermore, the following equation represents the two possible scenarios. Q_{MH}^{+} is the test statistic when the treatment effect is overestimated, and Q_{MH}^{-} is the test statistic when the treatment effect is underestimated:

$$Q_{MH}^{+(-)} = \frac{[\sum_{s=1}^{S}(Y_{1s} - \tilde{E}_s^{+(-)})]^2}{\sum_{s=1}^{S} Var(\tilde{E}_s^{+(-)})}, \tag{3.4}$$

where, according to Aakvik (2001), $\tilde{E}_s$ and $Var(\tilde{E}_s)$ are the large sample approximations to the expectation and variance, respectively, of the number of companies receiving treatment, Y_{1s}, when u is binary, and for a given Γ.

Appendix 3.C: Remaining Tables

Table 3.9. Variables definitions and sources

Variable	Definition	Source
No. of alliances $(t-1)$	Number of new strategic alliances in year $t-1$	S&P CIQ
Alliance dummy $(t-1)$	Dummy that indicates whether the company entered a new strategic alliance in year $t-1$	S&P CIQ
No. of alliances $(t-1/t-5)$	Number of new strategic alliances between years $t-5$ and $t-1$	S&P CIQ
Alliance dummy $(t-1/t-5)$	Dummy that indicates whether the company entered a new strategic alliance between years $t-5$ and $t-1$	S&P CIQ
No. of alliances $(t-2)$	Number of new strategic alliances in year $t-2$	S&P CIQ
No. of alliances $(t-3)$	Number of new strategic alliances in year $t-3$	S&P CIQ
No. of alliances $(t-4)$	Number of new strategic alliances in year $t-4$	S&P CIQ
No. of alliances $(t-5)$	Number of new strategic alliances in year $t-5$	S&P CIQ
VC rounds $(t-1)$	Number of VC rounds in year $t-1$	VS, TO
VC investors $(t-1)$	Number of VC firms investing in year $t-1$	VS, TO
VC new $(t-1)$	Number of outside investors to a certain company in year $t-1$	VS, TO
VC amount $(t-1)$	VC amount that was invested in year $t-1$ (USD mn)	VS, TO
VC network $(t-1/t-4)$	The average VC network of the VC firms that invested between years $t-4$ and $t-1$	VS, TO
Patents granted $(t-1/t-4)$	Number of patents that were granted between years $t-4$ and $t-1$	Patstat
VC network $(t-1)$	The average VC network of the VC firms that invested in year $t-1$	VS, TO
Patents granted $(t-1)$	Number of patents that were granted in year $t-1$	Patstat
...	...	...

Table 3.9. *continued*

Variable	Definition	Source
IPO exit	Dummy that indicates whether the company went public	VS, TO
M&A exit	Dummy that indicates whether the company was acquired	VS, TO
Foundation year	Year in that the company was founded	VS, TO
ln(Total VC rounds)	Log of the total number of VC rounds a company received in the period foundation until end of 2014	VS, TO
ln(Total VC amount)	Log of the total amount (USD mn) a company received in the period foundation until end of 2014	VS, TO
ln(Total investors)	Log of the total number of involved investors in a certain company in the period foundation until end of 2014	VS, TO
Total patents by appl.	Total number of patents by application date for a company in the period foundation until end of 2014	Patstat
VC network (mean)	Mean value of the total network of the involved investors in the period 2004 until 2014	VS, TO

Legend: S&P Capital IQ (S&P CIQ), Dow Jones VentureSource (VS), Thomson One (TO).

Chapter 4

The Role of Related Strategic Alliances before M&As[1]

Abstract

Based on M&A deals by companies from the biotechnology and pharmaceutical industry, I analyze the role of different types of prior ties between companies. I distinguish related alliances into direct and indirect alliances. Related alliances provide access to more information and can reduce transaction costs. The reduction of such costs can lead to a more successful target selection and a more efficient transaction process of the M&A deal because the time from announcement to completion can be reduced. This effect can be explained by trust-building, better access to private information, and certification through related alliances. However, in contrast to other studies, I do not find statistically significant evidence that supports the hypothesis that alliances increase the post-M&A performance and that alliances are associated with higher announcement returns.

JEL *classification:* G34, D74, D82

[1]This chapter is a single authored manuscript by the candidate.

4.1 Introduction

M&As are a channel for companies to grow, expand, enter new markets, and operate more efficiently. However, a proper target selection and post-merger integration are essential factors for a successful M&A (Bauer and Matzler 2014). The selection process before M&As is subject to information asymmetries and adverse selection because target companies do not always have the incentive to disclose detailed information. Besides, it is a priori not clear whether integration will lead to higher economies of scale because the success of the post-merger integration is uncertain. Strategic alliances can potentially reduce those risks and increase the probability of a subsequent successful M&A.

As argued in the literature, direct and indirect (economic) ties affect corporate outcomes. Harford et al. (2019) show that economic links between firms, such as trade relationships between customers and suppliers, are important and that such links can explain the pattern and impact on merger activity. Furthermore, Gulati (1995b) argues that indirect ties end in direct ties. Gulati (1995b) analyzes prior direct and indirect alliances and their effect on future alliances. My study extends such an analysis by examining the effect of prior direct and indirect alliances on the future M&A outcome. Moreover, I analyze the role of different types of related alliances before M&As. Furthermore, I distinguish between two types of prior ties (related alliances) that can be separated into direct and indirect alliances. First-degree ties are direct alliances, that is, the acquirer and the target company entered a strategic alliance before M&A announcement. Second-degree ties are indirect alliances.

Figure 4.1 illustrates these relationships in a small network. On the left-hand side of the figure, in a time prior to t_1, the acquirer A entered a strategic alliance with a company W, which is potentially a future target candidate. Later, the acquirer A acquires company W in t_1. The right-hand side of the figure depicts the situation with indirect alliances. Both companies, acquirer A and company V, have a strategic alliance with company X in a time prior to t_1. Then, acquirer A and company V do not have a direct relationship. However, because they have a common partner, both companies are indirectly connected, and company V might be a potential target candidate. Eventually, acquirer A acquires company V in t_1.

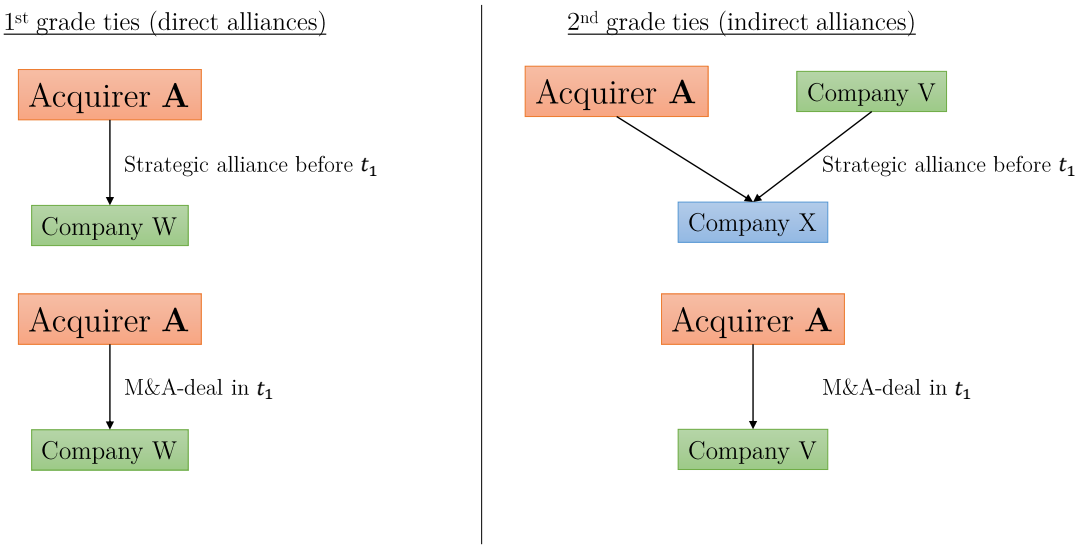

Figure 4.1. Prior alliance-ties

The acquirer company often lacks private information about potential targets, especially about private companies. Generally, this is because the acquirer company finds it difficult to estimate the correct value of the target's assets (see, e.g., Capron and Shen 2007). Furthermore, search difficulty increases with geographical distances (Chakrabarti and Mitchell 2013). Studies show that these frictions can be reduced by prior experience with M&As (Cuypers et al. 2017), or strategic alliances (see, e.g., Chang and Tsai 2013; Fang et al. 2015), and thus lead to more successful M&As and higher post-M&A returns. However, in these studies, the prior experience was measured as general experience with strategic alliances. My study contributes to the literature by distinguishing between direct and indirect alliances. In such cases, strategic alliances can potentially mitigate asymmetric information if the acquirer and target companies enter a strategic partnership before the transaction. Although alliances are seemingly beneficial for both companies, in practice, cases in which a strategic partner acquires the other partner rarely happen due to several reasons. According to Hagedoorn and Sadowski (1999), the "transition from strategic technology alliances to merger and acquisition hardly ever takes place." They report that 2.6% of strategic technology alliances end in an M&A. Further, in the study by He et al. (2018), less than 2% of M&A deals were deals where both companies had a previous strategic alliance. The decision to

enter a strategic alliance before an M&A is a trade-off between benefits and risks. Potential reasons why companies do not enter into alliances include, for example, the fear or risk of expropriation and moral hazard (Diestre and Rajagopalan 2012; Rothaermel 2001a;b; Rothaermel and Deeds 2004; Yang et al. 2014). Besides, M&As and strategic alliances are often considered as substitutes when it comes to the choice of governance. Gulati et al. (2009) show that prior alliances are associated more with future alliances than M&As. Villalonga and McGahan (2005) argue that the "history of dyadic ties" predicts the future choice of the type of deal that the firms will engage. That is, companies that have a (successful) history in strategic alliances will most likely choose strategic alliances over acquisitions in the future.

Due to the aforementioned risks, acquirer and target companies often do not ally before an M&A. However, from a theoretical perspective, strategic alliances have a positive impact on the probability that a deal occurs and on the efficiency of the transaction process. I propose that acquirers gain access to private information about a potential target directly and also indirectly through strategic alliances. Companies that entered into strategic alliances in the past share private information, which can lead to trust-building and eventually reduce transaction costs.

Other examples in the literature show that prior ties between the acquirer and target have a positive effect on the acquirer's post-M&A returns. For example, Higgins and Rodriguez (2006) show that prior access to information about research and development activities at the target company through pre-acquisition alliances is associated with the acquirer's positive returns. Cai and Sevilir (2012) analyze the role of prior board connections and demonstrate that such ties can facilitate communication and information flow between the acquirer and the target. Eventually, this can lead to higher announcement returns in transactions with prior ties between both parties.

Regarding post-M&A performance, there are mixed results in the literature. A recent study by He et al. (2018) shows a positive effect of prior direct alliances on return on assets, return on equity, and sales growth. However, a major limitation of the study by He et al. (2018) is that their analysis is based on a limited number of mergers with prior alliance ties and on a sample that includes different industries.

Prior alliance ties between the acquirer and target company are highly prevalent in the software or information technology industry, hence resulting in sample selection issues. Zollo and Reuer (2010) show that prior alliance experience has no direct effect on acquisition performance. Furthermore, Cho and Arthurs (2018) find a negative, but not significant effect of prior alliance experience on acquisition performance.

In this study, I focus on a sample of United States (US)-based companies from the biotechnology and pharmaceutical industry, including 940 M&A transactions from 1996 to 2014. Such sample construction has the following advantages. The acquirer companies operate in the same industry and are most likely similar in terms of development stage and operational targets. Furthermore, strategic alliances in the biotechnology and pharmaceutical industry are important because the results and output of these companies are associated with patents and are, therefore, essential for the company's success.

In nearly 12% of the cases, where both companies had at least one strategic alliance at the time of the announcement of the deal, the acquirer and target company were (or are) direct strategic partners. In around 17% of the cases, where both companies had at least one strategic alliance, the acquirer and the target had prior alliance-ties indirectly through other companies. To estimate the probability that one company acquires another company, I build different samples of counterfactual M&A deals, that is, deals that were possible but did not occur. I construct various samples of counterfactual deals that are based on different conditions, such as geography, or ownership of the target company. Furthermore, I am interested in the flow of information before the completion of M&A deals. If prior related alliances increase the information flow between the acquirer and target company, an M&A deal should be completed faster, compared to deals that do not have such prior ties. Finally, if the target selection and the transaction process is more efficient and successful with prior ties through related alliances, it should be visible in post-M&A performance and announcement returns.

This study contributes to the general literature on M&As and strategic alliances. In particular, this study contributes to the literature that deals with target selection in M&As and the role of strategic alliances on M&A success and performance. To my knowledge, this is the first study that distinguishes between

direct and indirect alliances, their relationship with each other, and their impact on M&As, unlike other studies that focus on the role of the position of companies in a general network. This study shows that related strategic alliances can mitigate the risks of asymmetric information, adverse selection, or moral hazard before M&As.

The remainder of the paper is structured as follows. The next section presents the theoretical background for this study and the derivation of the hypotheses. I discuss the dataset in Section 4.3, where I also provide descriptive statistics and the methodology I use to construct the sample of counterfactual alliances. In Section 4.4, I present the empirical results of the estimations. I discuss the results and their limitations in Section 4.5. Section 4.6 concludes.

4.2 Theoretical background and hypotheses

There are different reasons for companies to participate in M&As. For example, companies use M&As to grow and expand their businesses to gain from economies of scale. Other reasons can be entering a new (foreign) market, increasing market share, or improving its position among competitors. However, due to a certain degree of asymmetric information in the M&A process, especially if the acquirer is searching for a company to acquire, most of the time, the acquirer does not have full information about the target company. As an outsider, the acquirer must gain as much information as necessary (and possible) to decide whether or not to acquire a company. However, private information about a potential target is not easy to acquire. The target company may not be willing to share all their private information before an M&A is completed due to the possibility of exploitation. Furthermore, to determine the quality of information that the target company shares, it must be verified, which involves costs. However, in some cases, such transaction costs can be reduced through different means. One such mechanism is certification by a third party (Megginson and Weiss 1991). For example, investments by prominent VC investors can be viewed as a certification for the good quality of the portfolio company. Furthermore, observable resources can have a signaling function (Spence 1973). Hoenig and Henkel (2015) argue that patents, team experience, and strategic alliances can be a signal for unobservable

characteristics of a venture. However, the authors were unable to confirm that patents serve as signals. They rather find empirical evidence that alliances, and partly, team experience can be viewed as credible signals for unobservable company quality.

He et al. (2018) posit the hypothesis that a prior alliance relationship between the acquirer and the target company improves information sharing, builds trust, and eventually reduces information asymmetry. Repeated alliances between companies can reduce transaction costs of future alliances Gulati (1995a). Experience and repeated interaction between two companies can lead to trust-building, and hence, to a reduction in costs associated with information asymmetries or transactions. Besides, trust and familiarity between the acquirer and a potential target company can be important in a decision-making process, because public companies have shareholders that are involved in the decision of whether or not to acquire a company. Previous ties between both companies can be a positive signal to shareholders. Assuming that strategic alliances serve as signals and that alliances can potentially reduce transaction costs through access to broader information, M&A deals should be more likely to happen between parties that have prior ties. This leads to the first hypothesis:

Hypothesis 1a. *The probability of M&A increases when both parties have prior ties through direct strategic alliances.*

Previous literature argues that network embeddedness plays an important role in interorganizational relationships (Gulati 1995b; 1998; 1999; Walker et al. 1997; Yang et al. 2011; Zaheer and Bell 2005). Gulati (1995b) argues that the embeddedness in a network can facilitate new alliances and new ties. Previously unconnected companies are more likely to participate in new alliances if they have common partners. According to Gulati (1995b), such ties provide valuable information to firms about the specific capabilities and reliability of potential partners.

Furthermore, Ahuja (2000) posits that direct ties can provide access to resources and that they have knowledge-spillover benefits. However, direct ties, such as direct strategic alliances, incur costs, for example, maintenance or monitoring costs. On the contrary, indirect alliances are not associated with the same costs as direct alliances. As argued by Burt (2009), companies can benefit from

indirect ties similar to direct ties, but without having to bear the same costs. Finally, Ahuja (2000) argues that the benefits of indirect ties are most likely contingent on the existing number of direct ties, that is, companies benefit more from indirect ties when they do not have existing direct ties. This leads to the second hypothesis:

Hypothesis 1b. *An M&A is more likely when both parties have ties through indirect alliances and no direct alliances, and vice versa.*

Investment transactions, such as M&As or VC investments, are subject to information asymmetries between buyers and sellers, and transaction costs. Geographical distance is associated with access to information (see, e.g., Chakrabarti and Mitchell 2016; Coval and Moskowitz 1999; Sorenson and Stuart 2001) and additional risks and costs (Tykvová and Schertler 2014). Hence, transaction costs are positively correlated to the geographical distance between the acquirer and the target company. The acquirer collects information during due diligence before the M&A is completed. As a necessity, other sources of private information, such as strategic alliances, can potentially reduce the risks of adverse selection and information asymmetries (Reuer and Ragozzino 2008) that arise due to large geographical distance. Therefore, I posit that prior ties through direct or indirect alliances can reduce the difficulties arising from geographical distances. This leads to the third hypothesis:

Hypothesis 1c. *The probability of an M&A increases for companies from different states when both parties have ties through related alliances, compared to deals without such ties.*

The embeddedness in a well-connected network might induce trust among connected companies and have reputation effects (see, e.g., Raub and Weesie 1990; Uzzi 1996; Villalonga and McGahan 2005). Such connectedness can reduce costs, such as target selection and other related costs that are associated with the transaction process (Gulati 1995a). Therefore, because the M&A deal is subject to information asymmetries, trusting relationships can help complete a transaction faster due to better, broader, and faster access to private information through prior ties. This leads to the fourth hypothesis:

Hypothesis 2a. *The transaction process of an M&A deal is completed faster, that is, the time from the announcement of the deal to its completion is shorter, when the acquirer and the target company have prior ties through related alliances, compared to deals with no related prior ties between the acquirer and the target company.*

Sales of listed companies require the board of directors' approval, and shareholders need to ratify the transaction. Hence, the transaction process of an acquisition of a listed target might take a longer time than the acquisition of a private target. Building again on the theory of network embeddedness and creation of trust in repeated interactions between companies, I posit the fifth hypothesis that the time for the transaction of a listed target should be shorter for deals with prior ties through related strategic alliances.

Hypothesis 2b. *The transaction process of an M&A deal is completed faster, that is, the time from the announcement of the deal to its completion is shorter, if the target company is a public company, and the acquirer, as well as the target company, have prior ties through related alliances, compared to deals with no related prior ties and where the target company is private.*

Furthermore, according to Thomson SDC, cash payments were particularly more common in M&A deals than stock payments. One of the reasons is that stock payments are a more complicated way of paying for an acquisition than cash payments because the ownership status is not demarcated after the transaction. In addition, acquirer companies that pay with stocks also share the risks of the transaction of the company they acquire, and such transactions can affect shareholder returns. One can assume that the transaction process becomes more complicated with stock payments because more subjects are involved in the decision process. However, if companies share prior ties through related alliances, the trust and certification by prior ties can encourage a faster approval time, and thus, a faster transaction process. This leads to the sixth hypothesis:

Hypothesis 2c. *The transaction process of an M&A deal is completed faster, that is, the time from the announcement of the deal to its completion is shorter if the payment type is stock and both parties have prior ties through related alliances, compared to deals with no related prior ties and cash payment.*

If prior ties through related alliances allow companies to access additional private information about potential targets, this should reduce adverse selection problems, and thus, lead to a more efficient post-M&A integration. Familiarity in the operations of both companies and mutual trust can increase the success of the post-merger integration process. Furthermore, general alliance experience might be supportive for acquisitions, for example, due to experience spillovers and absorptive capacity (see, e.g., Cohen and Levinthal 1990; Zaheer et al. 2010; Zollo and Reuer 2010). Porrini (2004) argues that the experience with previous alliances may foster a more effective and efficient post-acquisition integration process, thus leading to better acquisition performance. Therefore, acquisition performance, such as return on assets or announcement returns, should be higher for deals where both parties shared prior ties through related alliances. This leads to the seventh and eighth hypotheses:

Hypothesis 3a. *M&A deals with prior ties through related strategic alliances are associated with higher post-M&A return on assets, compared to deals without related ties.*

Hypothesis 3b. *M&A deals with prior ties through related strategic alliance are associated with higher announcement returns, compared to deals without related ties.*

4.3 Data

4.3.1 Sample selection

The sample contains all M&A deals between 1990 and 2014 of US-based acquirers. Further selection criteria are: (i) announcement date between January 1, 1996, and December 31, 2014; (ii) the acquirer is a publicly-traded US company; (iii) the percentage of shares sought in the deal is at least 50%; (iv) the deal is not a joint venture, spin-off, recapitalization, self-tender, exchange offer, repurchase, or privatization; (v) the acquirer company operates in either the biotechnology or pharmaceutical industry; and (vi) the data can be matched to CRSP stock information at the time of the announcement and Compustat financial data.

I collected the data on strategic alliances from Thomson SDC for each acquirer and target company. In the overall dataset, 71% of the acquirer companies and 27% of the target companies have at least one (related or unrelated) strategic alliance at the time of the announcement of the M&A. The acquirer companies with at least one strategic alliance have, on average, 21 strategic alliances, and the target companies have, on average, 4.7 strategic alliances.

Table 4.1 shows summary statistics for realized deals in the overall sample of 940 deals. The average number of days from the announcement to the completion of the deal is around 54. The difference between the return on assets three years after and one year before the focal acquisition is, on average, -0.3546. Cumulative abnormal returns (CARs) of the acquirer in the event window (–2,+2) and (–5,+5) around the deal announcement date are, on average, around 0.009 and 0.007, respectively. On average, in 23% of the deals, both companies had at least one strategic alliance (related or unrelated). In around 3% of the deals, both companies had a prior direct alliance with each other. In around 4% of the deals, the companies were connected through indirect alliances. For all deals, there were, on average, 0.1 indirect alliances, whereby the maximum number of indirect alliances is 13. In 77% of the cases, a private company was acquired and in 22% of the cases, a non-US target was acquired. In 21% of the deals, both companies were located in the same US-state. The variable *Payment* is a factor variable and takes on the values 1 for cash payment, 2 for mixed payment, 3 for stock payment, and 4 for other payment. A total of 250 deals were paid with cash (26.60%). In 120 deals, the payment type was mixed (12.77%), and in 198 deals, the payment type was stock (21.06%). The remaining 262 deals were paid by another payment type (27.87%). For 110 deals, the payment type was undisclosed (11.70%). The sample contains control variables for deal characteristics. Five different variables indicate whether the deal was a hostile takeover, a divestiture, a tender offer, an unsolicited deal, or started as a rumor.

4.3.2 Creation of counterfactuals and descriptive statistics

It is necessary to have variation in the dependent variable to estimate the relationship between two variables, or the effect of one variable on another. This study

analyzes whether prior ties through strategic alliances are related to the probability of an M&A. However, I can only observe deals that were realized in the past. Therefore, I need data in the sample that depicts counterfactual deals, that is, deals that were possible but did not happen, and hence, create variation in the dependent variable. The challenge is to construct counterfactual deals where only one factor—the fact that one deal was realized and the other was not—differs, and other characteristics remain the same or very similar. In practice, most of the time this is difficult to construct, because I can only include variables that are observable. For that reason, I construct different counterfactual samples that vary in terms of restrictions to the main sample. With such restrictions, I can eliminate, or at least, mitigate potential biases from unobservable characteristics, and hence, confirm the robustness of the estimation results.

Counterfactual deals are based on a function that maps the elements of $\boldsymbol{Y}$ to $\boldsymbol{X}$. The codomain $\boldsymbol{Y}$ is the set of all target companies, and the domain $\boldsymbol{X}$ contains all acquirer companies from M&A deals between 1996 and 2014 in the biotechnology or pharmaceutical industry. Furthermore, the function maps six elements of $\boldsymbol{Y}$ for each element in $\boldsymbol{X}$, under the condition that the announcement dates of those deals in $\boldsymbol{Y}$ are the closest in time to the actual announcement date of elements in $\boldsymbol{X}$.

Figure 4.2 illustrates the mapping. As an example, consider acquirer company **A**, which closed an M&A deal with target company **P**. There were also other M&A deals in the biotechnology and pharmaceutical industry around that time. The sequence n is sorted by the announcement time of the deals. The target companies M, N, O, Q, R, and S, are considered to be potential target companies for the acquirer company **A**.

To estimate the relationship between strategic alliances and the probability of an M&A, I create three different samples of counterfactual deals. In the first sample, I only include biotechnology and pharmaceutical companies. For each pair of acquirer and target, that is, an actual M&A deal, I create counterfactual deals that were potentially possible at that time but did not happen. Given that I only consider biotechnology or pharmaceutical companies, it is reasonable to assume that target companies in timely close deals were also possible targets for the acquirer companies in actual deals. The second sample is restricted to US-

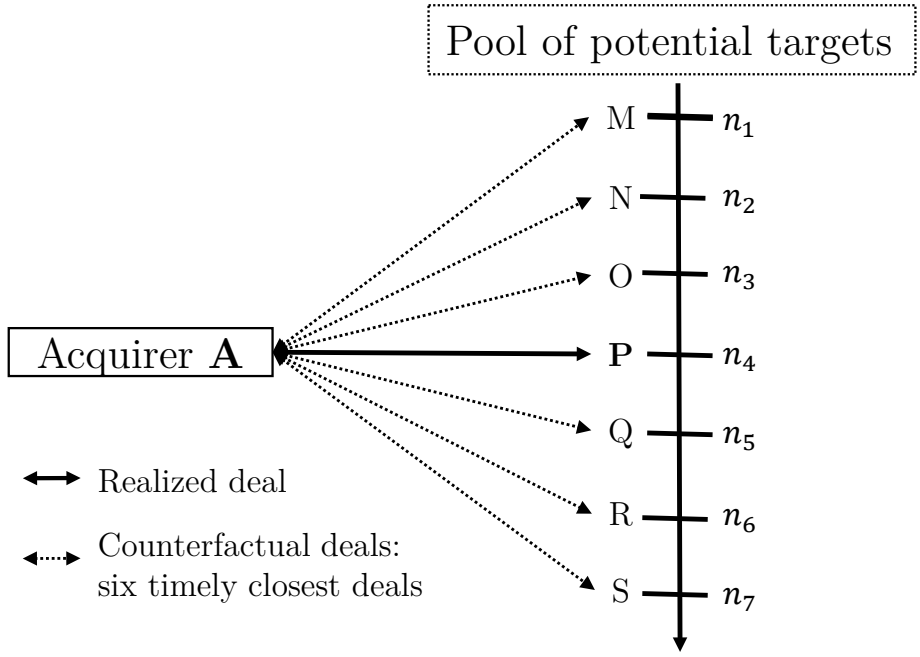

Figure 4.2. Counterfactual deals built by mapping potential targets to acquirers

based targets, that is, domestic deals. With such a restriction, it is possible to mitigate cultural distances and account for geographical distance precisely. Finally, the third sample contains only listed target companies.

Table 4.2 shows summary statistics for different counterfactual samples. Panel A contains the most deals (940). Panel B, which restricts the sample to US-based target companies, contains 737 realized deals. The smallest sample is Panel C, which contains 189 realized deals and further restricts the sample to only public US-based target companies. The mean value of the dependent variable *Realized deal* is equal to 0.1429, because, in all the three panels, the number of counterfactual deals that are matched to each realized deal is the same.

4.4 Results

4.4.1 The probability of a successful M&A

Table 4.3 shows partial effects at the averages of logistic regressions for different panels. The first panel of the counterfactual sample contains 940 realized and 5,640 counterfactual deals. As a reference category, I include a dummy variable that equals one if both companies entered at least one related or unrelated strategic alliance, and zero otherwise. With such a setting, it is possible to estimate the additional effects of related alliances. In columns 1, 2, 3, and 4, the coefficient of *Dummy both alliance* is statistically significant and positive. Hence, when both companies engage in previous unrelated or related strategic alliances, those company pairs are, on average, associated with a 2 to 3.5 percentage points higher probability of a completed M&A deal.

Furthermore, I include measures for related strategic alliances in the next estimations. The variable *Dummy direct alliance* equals one if both companies participated in a strategic alliance with each other before the M&A, and zero otherwise. The next two variables capture prior ties through indirect strategic alliances. *Dummy indirect alliance* equals one if there was at least one indirect strategic alliance between both companies, and zero otherwise. The variable *Number indirect alliances* counts the number of indirect strategic alliances before the M&A. In all the estimations, the coefficients of the measures for related strategic alliances are statistically significant and positive, thus indicating a positive relationship between the completed M&A and related strategic alliances. *Dummy direct alliance* is associated with a 39 percentage points higher likelihood that an M&A will be completed (column 2) and *Dummy indirect alliance* is associated with around 12 percentage points higher likelihood that an M&A will be completed (column 3), compared to the reference category. When both measures are included in one estimation (column 4), the coefficients remain statistically significant and positive, meaning that both types of related alliances are associated with a higher probability of completed M&As. In the last two estimations (columns 4 and 5), I replace the dummy variable that measures indirect strategic alliances with a count variable for indirect strategic alliances. The coefficient of the variable *Number indirect al-*

liances is statistically significant and positive thus indicating that a higher number of prior ties through indirect strategic alliances is associated with a higher probability of a completed M&A. In all the estimations, I control for private targets, cross-border deals, and year fixed effects. However, the coefficients of the variables of *Private target* and *Cross-border deal* are statistically not significant.

Panel B shows the results for a subsample that contains only US-based target companies. This sample includes 737 realized and 4,422 counterfactual deals. I use this sample to control whether related alliances are associated with a higher likelihood of completed M&As when controlling for distance. It is possible to include a distance variable in the previous sample; however, this would be somewhat problematic because, for example, the distance between the US and Europe is significant, compared to the distances within the US. This would lead to biased results because of the distribution of the distance variable.

Similar to the previous estimations with Panel A, I include a dummy variable that equals one if both companies entered into at least one related or unrelated strategic alliance, and zero otherwise. The coefficient of the variable *Dummy both alliance* is statistically significant and positive in all columns except for column 4. The measures for related strategic alliances are statistically significant and positive in all regressions, except for column 6, where the coefficient of the variable *Number indirect alliances* is statistically not significant. Further, the magnitudes of the coefficients are similar to the results in the previous estimations with Panel A, thus indicating robust results. This illustrates an important association between related alliances and the probability of a successful M&A deal. Another result is that when both companies are located in the same US-state, the probability of a completed M&A deal increases by around 12 percentage points. The coefficients of the variable *Same state* stay similar in statistical significance and magnitude in all regressions.

Panel C of Table 4.3 shows the results for the subsample with M&A deals where the target companies were listed on the stock exchange and their headquarters located in the US. The sample contains 189 realized and 1,134 counterfactual deals. This setting excludes the effects of cross-border and private target deals. Contrary to the estimations in Panel A and Panel B, the coefficient of the variable *Dummy both alliance* is not statistically significant in any of the regression models. How-

ever, the coefficients of the dummy variables that measure the involvement of either direct or indirect strategic alliances are statistically significant. In this scenario, the coefficients are somewhat smaller in magnitude than the estimations in the other two panels. When both measures of direct and indirect strategic alliances are included in one regression model, the statistical significance of the indirect strategic alliance measure disappears. One explanation of this result can be that listed companies are more transparent because they have much higher reporting and disclosure requirements. Hence, such deals do not need many certifications through third parties, for example, through direct or indirect alliances. Another result is that distance still matters, and the coefficient of the variable *Same state* is statistically significant at the 5 percent level.

To sum up, the results from Table 4.3 provide empirical support for Hypothesis 1a. Direct alliances might play an important role in the completion and success of M&A deals because they are associated with a higher likelihood of an M&A. In most estimations, this is also the case regarding indirect alliances. However, in the analysis in Panel C, where the target company is already a listed company, indirect strategic alliances do not have a statistically significant effect on the probability of an M&A, and other effects might better explain the choice of the target and the success of an M&A.

To test the next hypothesis, it is suitable to include interaction terms in an ordinary least squares (OLS) setting. Such an analysis allows me to estimate the relationship of the outcome of one independent variable on another independent variable. In this case, by the assumption of Hypothesis 1b, I would expect a negative and statistically significant coefficient of the interaction variable between direct and indirect alliances. Table 4.4 shows the results of OLS estimations with interaction terms between the variables for direct and indirect strategic alliances for Panels A, B, and C. The variables *Dummy direct alliance*, *Dummy indirect alliance*, and *Number indirect alliances* show statistically significant and positive coefficients in all settings. Furthermore, the interaction term between the variables *Dummy direct alliance* and *Dummy indirect alliance* are negative and statistically significant in Panels B and C (columns 3 and 5). The interaction term between *Dummy direct alliance alliance* and *Number indirect alliances* are negative and statistically significant in Panels A and B (columns 2 and 4). To sum up, these

results show empirical evidence for Hypothesis 1b, which states that M&A deals are more likely when only indirect or only direct ties are present, which is consistent with the results of Ahuja (2000).

In the next step, I analyze the influence of geographical distance on the probability of an M&A. Table 4.5 shows OLS results with interaction effects. The underlying sample is Panel B, where the condition is that the target companies are US-based only. With such restriction, the bias resulting from cultural distances and differences between the companies can be mitigated to a certain extent. All estimations contain the variable *Not same state*, which serves as the reference category and indicates whether both companies are located in different US-states. The coefficient of this variable is negative and statistically significant in all settings, thus, showing a negative empirical relationship between geographical distance and the probability of an M&A deal. Companies that are located in distant cities are more likely to have difficulties evaluating a potential target company than companies that are located near its headquarters. Table 4.5 shows that a larger geographical distance is associated with a lower likelihood of an M&A. The coefficient of the variable *Dummy both alliance* is statistically not significant in column 1 and the interaction term between *Dummy both alliance* and *Not same state* is statistically not significant. However, when controlling for related alliances, the coefficient of the variable *Dummy both alliance* becomes statistically significant in all remaining specifications (columns 2 to 4). Furthermore, the interaction term between *Dummy direct alliance* and *Not same state* is statistically not significant (column 2). Finally, the interaction terms between *Dummy indirect alliance* and *Not same state*, and between *Number indirect alliances* and *Not same state*, are positive but statistically not significant. To sum up, there is not enough evidence for a clear relationship between related alliances and geographical distances, and no empirical evidence for a moderating effect of prior ties on geographical distance. Thus, Hypothesis 1c cannot be confirmed with this empirical analysis.

4.4.2 The time to a successful completion of an M&A deal and the type of payment

Figure 4.3 shows the distribution of the time between the announcement date and the completion date of an M&A deal. Time is measured in days. The distribution is right-skewed with many deals that were completed on the announcement day.

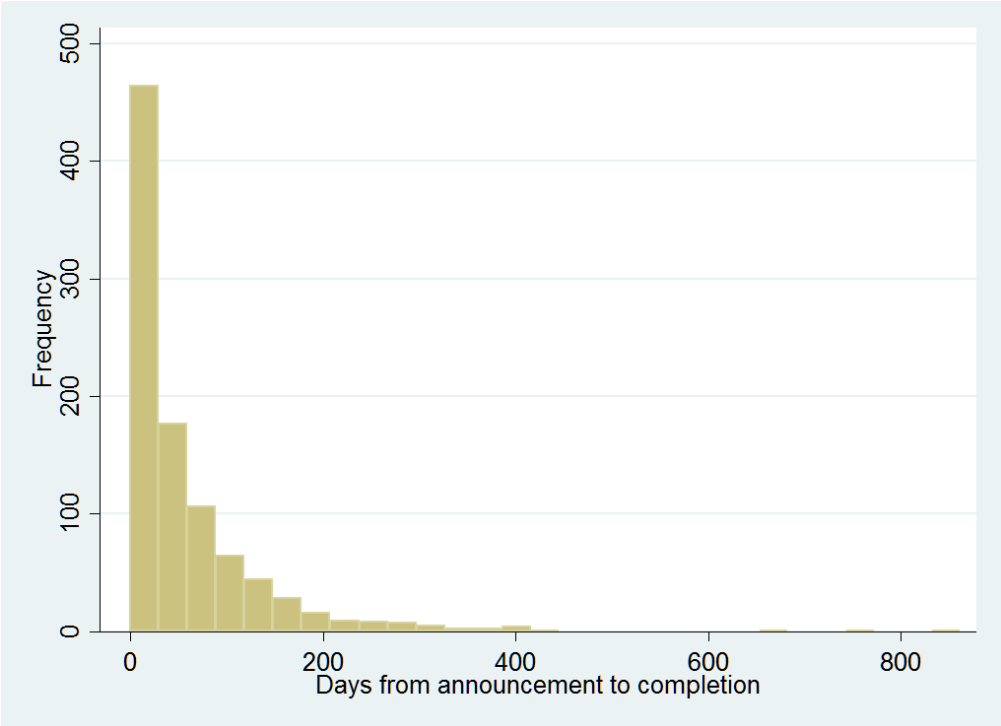

Figure 4.3. Time to completion of an M&A deal

Related alliances could reduce information asymmetries and increase the speed of information flows, thus reducing the time to completion of a deal. Given that the time to completion is always non-negative, it is reasonable to estimate the relationships by applying a count data model.

The conditional expectation of the number of days from announcement to completion y is given by

$$E(y_i|\boldsymbol{x}_i) = exp(\boldsymbol{x}_i\boldsymbol{\beta}) = \mu_i, \tag{4.1}$$

where μ is the mean parameter. This assumption of such a relationship between

the mean and the regressors ensures that the expected number is non-negative. Furthermore, from the Poisson distribution and the parametrization of the relation between the mean and the regressors, the probability that y takes on the value h, conditional on $\boldsymbol{x}$ is given by

$$P(y_i = h_i|\boldsymbol{x}_i) = \frac{exp[-exp(\boldsymbol{x}_i\boldsymbol{\beta})][exp(\boldsymbol{x}_i\boldsymbol{\beta})]^{h_i}}{h!}. \tag{4.2}$$

The log-likelihood function $\mathscr{L}$ for the observed sample with size N is given by

$$\mathscr{L}(\boldsymbol{\beta}) = \sum_{i=1}^{N}\{y_i\boldsymbol{x}_i\boldsymbol{\beta} - exp(\boldsymbol{x}_i\boldsymbol{\beta}) - \log(y_i!)\}. \tag{4.3}$$

Maximizing the log-likelihood function with respect to β yields the Poisson maximum likelihood estimation that is denoted as $\hat{\beta}_P$. The great advantage of the Poisson model is its consistency, even if the data is not distributed according to the Poisson distribution (Cameron and Trivedi 2005: p. 669). The important assumption is that the conditional mean $E(y_i|\boldsymbol{x}_i)$ is correctly specified. Such maximum likelihood estimations in case the density is misspecified, are called pseudo-maximum likelihood or quasi-maximum likelihood estimation. For the Poisson model, the K non-linear equations that are the first-order conditions for the log-likelihood function are given by

$$\sum_{i=1}^{N}\boldsymbol{x}_i'[y_i - exp(\boldsymbol{x}_i\hat{\boldsymbol{\beta}})] = 0. \tag{4.4}$$

If the conditional mean is correctly specified, that is, $E(y_i|\boldsymbol{x}_i) = exp(\boldsymbol{x}_i\boldsymbol{\beta})$, and a constant is included in $\boldsymbol{x}$, the summation on the left-hand-side of Equation 4.4 has expectation zero, and hence, the Poisson pseudo-maximum likelihood is consistent. The variance-covariance matrix is given by the negative inverse of the second derivative of the log-likelihood function.

By taking the log of Equation 4.1, the estimated coefficients can be directly

interpreted. Because the first derivative is

$$\frac{\partial \log[E(y_i|\boldsymbol{x}_i)]}{\partial x_j} = \beta_j, \tag{4.5}$$

the semi-elasticity of $E(y_i|\boldsymbol{x}_i)$ with respect to x_j is given by $100\beta_j$.

Table 4.6 shows the results of the quasi-maximum likelihood estimation. All the estimations contain the variable *Dummy both alliance*, which serves as the reference category. Controlling for direct alliances by the variable *Dummy direct alliance* shows that the coefficient is negative but statistically not significant (column 1). Further, the coefficient of the variable *Dummy indirect alliance* is positive but statistically not significant (column 2). In estimation (3), the effect of the number of indirect alliances is statistically significant and positive, thus, indicating that indirect alliances are positively related to the number of days between announcement and completion. However, in estimation (4) of Table 4.6, both measures (direct and indirect alliances) are included in the estimation, and the coefficient of the variable *Dummy direct alliance* becomes statistically significant. Therefore, a direct alliance between the acquirer and the target company is associated with a 64% decrease in the expected number of days between announcement and completion of an M&A deal, compared to the reference category. This could indicate that direct alliances become more valuable when there are ties through indirect alliances also. Another explanation could be that a deep connectedness of the target company can be beneficial in the transaction process. However, Hypothesis 2a is only confirmed for deals with prior ties through direct alliances.

Furthermore, the coefficient of the dummy variable that measures whether the target company was a listed company is positive and statistically significant. In most cases, the transaction process of acquiring a listed company is more complicated than a private target because more people and decision-makers are involved in the process. Moreover, the M&A deal must be approved by the shareholders. Another explanation for this effect could be that listed companies are obligated to announce such important events as soon as possible, whereas the announcement of an acquiring process of a private target can be held back for a more extended period.

Another important result is the type of payment. In all the estimations, the

reference category is cash payment. Stock payment is associated with a longer time period from announcement to completion, while *other* payment is associated with a decrease in the time between announcement and completion, compared to the reference category.

In the next step, I examine the various interaction effects between the different alliance ties and other important control variables. Table 4.7 shows the results of OLS estimations with interaction terms. Public targets are associated with a longer deal transaction process because the coefficient of the variable *Public target* is positive and statistically significant (columns 1 to 4). However, prior related alliances should be beneficial because direct or indirect alliances can be an indicator for trust between both companies, given that they are in a business relationship (direct alliance), or they share common strategic partners (indirect alliances). Furthermore, the interaction term shows that the expected number of days between announcement and completion decreases when there are prior ties through indirect alliances (column 2). Prior indirect ties and the acquisition of a public target are associated with a shorter time from announcement to acquisition. This result indicates the importance of the connectedness of the target companies. A well-connected target company is also known to more shareholders, and thus, could decrease the time of the shareholder approval process. The coefficient is statistically significant at the 1% level. However, although the coefficient of the interaction term between *Dummy direct alliance* and *Public target* is also negative, it is statistically not significant (column 1). The results confirm Hypothesis 2b only for deals with prior ties through indirect alliances.

The type of payment for the acquisition is an important factor that influences the time to completion. Table 4.6 showed that in cases where the payment type is *stock*, the time to completion significantly increases by around 50%, compared to *cash* payment. However, the outcome of the type of payment is also related to prior alliance ties. If prior ties induce trust between the acquirer and the target company, the shareholders could be more willing to accept the payment type *stock*, which is associated with an increase in capital. The estimations show that the coefficient of the variable *Payment (stock)* is positive and significant, which implies that the time to completion is longer. However, this result must be interpreted with caution because an interaction term is included in the estimation. Therefore, this result is

only valid when there are no prior direct alliances. If there are prior direct alliances, then the overall effect is negative, hence, a shorter time to completion, because the coefficient of the interaction term between the payment type *stock* and a prior direct alliance is negative and statistically significant (column 3). Prior direct ties can decrease the time to completion for deals with stock payment. Indirect alliances and the payment type *mix* are associated with an increase in the time to completion (column 4). Hypothesis 2c is only confirmed for deals with prior ties through direct alliances.

Regarding the choice between the payment type *cash* and *stock*, Table 4.8 shows the results of logistic regressions, where the dependent variable equals one if the type of payment was *stock*, and zero if the type of payment was *cash*. The main result is that the presence of prior ties through direct strategic alliances is associated with a higher likelihood of *cash* payment compared to *stock* payments (columns 1 and 4). In estimations (2) to (4), the coefficients of the variables that measure prior ties through indirect alliances are statistically not significant, and thus, are not associated with the choice of the type of payment.

4.4.3 The role of related alliances on post-M&A performance and announcement returns

Table 4.9 presents the results of the first analysis, which focused on the role of related alliances on post-M&A performance. The dependent variable is a measure of the return on assets and is calculated as the difference between the return on assets three years after and one year before the focal acquisition. This measure is a common measure for M&A performance in the literature (see, e.g., Cho and Arthurs 2018; Healy et al. 1992; Zollo and Reuer 2010).

The OLS estimations indicate no statistically significant relationship between the return on assets and related strategic alliances. Throughout all the estimations and settings, the coefficients of the variables that indicate prior ties are positive but not significant. In addition, the coefficients of the control variables are all statistically significant.

Table 4.10 shows OLS estimations, where the dependent variable is a calculation of CARs using the market model. Columns 1 to 4 show the results of the

event study, where the event window is −2 and +2 around the announcement day of the deal (in %). Besides, I run regressions with a wider event window (−5, +5). The estimation period for all regression is −300 and −91 days. The effects of related alliances on CARs are positive; however, the coefficients are statistically not significant. Other control variables, such as *Public target*, *Hostile takeover*, or *Cross-border deal* do have a statistically significant negative effect on CARs around the announcement date of the deal.

To sum up, with this empirical setting, it cannot be shown that there is a significant relationship between the presence of prior ties through strategic alliances and post-M&A performance measures, such as return on assets, or CARs around the announcement date of the deal. Thus, Hypothesis 3a and 3b cannot be confirmed with these empirical results.

4.5 Discussion and limitations

The main results of the first part of the empirical analyses show that there is a significant relationship between the likelihood of an M&A and prior ties through related strategic alliances. There are several explanations for the underlying results. First, access to private information can have a positive effect on the valuation and selection of a potential target, as uncertainties about a future target, and thus, transaction costs can be reduced. Hence, prior ties can lead to a more efficient acquirer-target matching and a better fit between both companies. Furthermore, the embeddedness in a network can explain the choice of the future target. Prior ties through direct alliances enhance trust between both parties, and indirect alliances serve as a certification or quality signal. If a common strategic partner was shared between the acquirer and target company, it can serve as a certification for good quality through a third party.

Regarding the role of related alliances in the time to completion of an M&A deal, the results are not clear-cut. At first glance, direct alliances do not have a statistically significant effect on the time to completion of an M&A. Indirect alliances even seem to increase the time from announcement to completion, thus increasing the time of the transaction process. However, when analyzing the relationships in more detail, other vital results emerge. For example, when including

both measures of related alliances, the effect of direct alliances becomes significant. Furthermore, indirect alliances might play an important role in the acquisition of a public target because they can reduce the time of the transaction process owing to a familiar relationship between the acquirer and the target company. Moreover, when it comes to the type of payment, indirect alliances might be beneficial when the acquisition is paid by stocks. One explanation can be that the reputation of a well-connected target company might increase the speed of approval by the board of directors and shareholders, as the target company is well-known.

The final empirical analysis of this study examines the role of related alliances on post-M&A performance. First, the analysis shows that there is no statistically significant link between related alliances and M&A performance. The M&A performance is measured by the difference between the return on assets three years after and one year before the focal acquisition. The result is supported by previous empirical studies, for example, by Cho and Arthurs (2018), who also do not find any significant effect of alliances on post-M&A return on assets. Second, the findings in this study do not show a statistically significant difference between announcement returns of deals with and without related alliances. One explanation can be that the effects of any strategic alliance are already priced into the stock before the M&A announcement.

The challenge of this study is the empirical setting and the establishment of a causal link between related alliances and M&As. Different counterfactual samples were built to eliminate or reduce some of the unobservable factors. The estimations with different counterfactual samples show similar results. Furthermore, the relationship between related alliances and the likelihood of M&As seem to be robust. Nevertheless, there might be concerns about the creation of the counterfactuals. I built different counterfactuals to reduce bias risks. However, there are also other possible ways of constructing the samples, for example, by random matching.

The empirical analyses in this study are subject to various limitations. One of the potential problems is self-selection by companies. Target companies with better quality or a more promising future might choose related alliances to signal sound quality. Therefore, the higher probability of an M&A for companies with prior ties can also be explained by self-selection. However, since the characteristics of a promising future, such as the talent of the entrepreneur of the target company,

are often not observable, the empirical results are subject to bias. In addition, as information asymmetries are present between the buyer and seller, the results, as well as the causal link between the probability of an M&A and related alliances, must be interpreted with caution. The solutions to these issues might be to use other empirical methods, such as instrumental variable regressions or propensity score matching, which can reduce the bias to a certain amount.

Another potential bias can be the similarity of both companies. An M&A between two companies might be more likely when the two companies are similar or share a common or suitable corporate strategy, and thus, make a good fit. This can be a driving factor of the selection into an M&A, rather than prior ties through related alliances. However, such empirical shortcomings are often challenging to overcome, as many factors are unobservable.

The last part of the empirical analyses is affected by technical shortcomings. There is no consensus in the extant literature about the best way to measure M&A performance (see, e.g., King et al. 2004). Measuring the effect of post-M&A performance by the difference between the return on assets three years after and one year before the focal acquisition might be subject to bias, as the accounting of the assets after the acquisition might already include the assets of the target company. Finally, the event study method is also vulnerable to confounding conditions.

4.6 Conclusion

The role of strategic alliances before M&As is not straightforward. This study showed that in some ways, not only direct but also indirect alliances play an important role in the M&A transaction process. The empirical results confirm some of the hypotheses that alliances can enhance the efficiency of target selection and decrease transaction costs. However, one has to distinguish between different types of prior ties, as not only direct ties but also indirect ties can affect the outcome of an M&A. The results have importance from a practical perspective also. Prior ties through strategic alliances can be a good predictor for the outcome of the M&A and the time of the transaction process. Managers from acquiring companies can use their network of strategic alliances to find future potential target companies. Moreover, entrepreneurs of target companies can use the information

that they acquire through related alliances.

Future research studies could extend this analysis in several ways. For example, future studies could expand the sample and include deals from other countries and different industries. In addition, the analysis could be extended to higher grades of prior ties. The effect of prior ties might decrease with higher grades of connections. Furthermore, as the construction of the counterfactuals is one of the main challenges in such empirical analysis, it would be worthwhile to extend the number of counterfactual samples. For example, one way would be to randomly select potential targets to actual deals. Another approach would be to restrict the pool of potential targets using several factors, such as industry, age, and other company characteristics. Moreover, an interesting way would be to match peers or competitors of the actual target as potential targets. However, this method would be subject to data availability issues because most of the target companies are privately held.

Finally, the way of identification of the causal link could be improved by applying other empirical methods and research designs, such as instrumental variable regressions or company survey analysis. Yet, the first method will need valid instruments, and the second method a sufficient number of observations.

Appendix 4.A: Tables

Table 4.1. Summary statistics: realized deals

	#obs.	mean	s.d.	min	max
Time to completion	940	53.6532	80.6294	0	862
$\Delta ROA_{(t+3)/(t-1)}$	560	-0.3546	23.4345	-445.8625	294.3645
CAR$[-2,+2]$	608	0.0086	0.1262	-0.4054	1.4344
CAR$[-5,+5]$	608	0.0074	0.1600	-0.5676	1.7071
Dummy both alliance	940	0.2255	0.4182	0	1
Dummy direct alliance	940	0.0277	0.1641	0	1
Dummy indirect alliance	940	0.0372	0.1894	0	1
Number indirect alliances	940	0.0777	0.5721	0	13
Private target	940	0.7660	0.4236	0	1
Cross-border deal	940	0.2138	0.4102	0	1
Same state	940	0.2117	0.4087	0	1
Payment	830	2.5687	1.2169	1	4
Hostile takeover	924	0.0022	0.0465	0	1
Divestiture	924	0.0152	0.1222	0	1
Tender offer	924	0.0617	0.2407	0	1
Unsolicited	924	0.0076	0.0868	0	1
Rumor	940	0.0223	0.1479	0	1

Legend: This table shows descriptive statistics for different variables that are calculated by the time of the announcement of the M&A deal. *Time to completion* is non-negative and counts the days between the announcement and completion date of an M&A deal. $\Delta ROA_{(t+3)/(t-1)}$ is the difference between the return on assets three years after and one year before the focal acquisition. $CAR[-2,+2]$ and $CAR[-5,+5]$ are cumulative abnormal return of the acquirer in the event window $(-2,+2)$, respectively $(-5,+5)$, around the deal announcement date. *Dummy both alliance* is a dummy variable that equals one if the acquirer and the target company had at least one strategic alliance (unrelated or related) prior to the M&A deal, and zero otherwise. *Dummy direct alliance* is a dummy variable that equals one if the acquirer and the target company had a direct strategic alliance prior to the M&A deal, and zero otherwise. *Dummy indirect alliance* is a dummy variable that equals one if the acquirer and the target company had an indirect strategic alliance prior to the M&A deal, and zero otherwise. *Number indirect alliances* counts the number of indirect alliances between the acquirer and the target company. *Private target* is a dummy variable that equals one if the target was a private company prior to the M&A deal, and zero otherwise. *Cross-border deal* is a dummy variable that equals one if the target was a non-US company, and zero otherwise. *Same state* is a dummy variable that equals one if the acquirer and the target company were in the same US-state, and zero otherwise. *Payment* is a factor variable and takes on the values 1 for cash payment, 2 for mixed payment, 3 for stock payment, and 4 for other payment. *Hostile takeover* is a dummy variable that equals one if the deal is characterized as a hostile takeover, and zero otherwise. *Divestiture* is a dummy variable that equals one if the M&A deal was a divestiture sale, and zero otherwise. *Tender offer* is a dummy variable that equals one if the acquirer offers its stock in the M&A deal, and zero otherwise. *Unsolicited* is a dummy variable that equals one if the offer was unsolicited, and zero otherwise. *Rumor* is a dummy variable that equals one if the M&A deal started as a rumor, and zero otherwise.

Table 4.2. Summary statistics: realized deals and counterfactuals

	Panel A			Panel B		
Observations	RD 940	CF 5640	t-value	RD 737	CF 4422	t-value
Dummy both alliance	0.2255	0.1871	-2.7709	0.2483	0.1952	-3.3251
Dummy direct alliance	0.0277	0.0012	-10.7061	0.0299	0.0016	-9.5854
Dummy indirect alliance	0.0372	0.0138	-5.1229	0.0475	0.0149	-5.9267
Number indirect alliances	0.0777	0.0215	-5.3741	0.0991	0.0258	-5.1445
Same state	0.2117	0.0927	-10.9003	0.2619	0.1185	-10.5264
Private target	0.7660	0.7683	0.1550	0.7436	0.7463	0.1566
Cross-border deal	0.2138	0.2142	0.0245	–	–	–

	Panel C		
Observations	RD 189	CF 1134	t-value
Dummy both alliance	0.6349	0.5952	-1.0310
Dummy direct alliance	0.0794	0.0132	-5.7199
Dummy indirect alliance	0.1429	0.0820	-2.7021
Number indirect alliances	0.3280	0.1570	-2.7086
Same state	0.1852	0.1340	-1.8697

Legend: This table shows descriptive statistics. Column *RD* shows the mean values for different variables from samples of realized deals. Column *CF* shows the mean values for different variables from the sample with counterfactual deals. Column *t-value* shows the t-value from a t-test between the values from *CF* and *RD*. Panel A is a subsample that contains only acquirer companies from the biotechnology or pharmaceutical industry. Panel B restricts the subsample to US-based target companies. Panel C contains only listed US-based target companies. *Dummy both alliance* is a dummy variable that equals one if the acquirer and the target company had at least one strategic alliance (unrelated or related) prior to the M&A deal, and zero otherwise. *Dummy direct alliance* is a dummy variable that equals one if the acquirer and the target company had a direct strategic alliance prior to the M&A deal, and zero otherwise. *Dummy indirect alliance* is a dummy variable that equals one if the acquirer and the target company had an indirect strategic alliance prior to the M&A deal, and zero otherwise. *Number indirect alliances* counts the number of indirect alliances between the acquirer and the target company. *Private target* is a dummy variable that equals one if the target was a private company prior to the M&A deal, and zero otherwise. *Cross-border deal* is a dummy variable that equals one if the target was a non-US company, and zero otherwise. *Same state* is a dummy variable that equals one if the acquirer and the target company were in the same US-state, and zero otherwise.

Table 4.3. Probability of an M&A deal: estimations with counterfactuals

Panel A: Acquirer is from the biotechnology or pharmaceutical industry

DV: Realized deal	(1)	(2)	(3)	(4)	(5)	(6)
Dummy both alliance	0.0352***	0.0205*	0.0240**	0.0113	0.0270**	0.0136
	(0.0113)	(0.0117)	(0.0119)	(0.0122)	(0.0117)	(0.0121)
Dummy direct alliance		0.3905***		0.3796***		0.3801***
		(0.0566)		(0.0582)		(0.0580)
Dummy indirect alliance			0.1154***	0.1015***		
			(0.0270)	(0.0292)		
Number indirect alliances					0.0523***	0.0484***
					(0.0154)	(0.0159)
Private target	0.0121	0.0142	0.0160	0.0174	0.0158	0.0173
	(0.0111)	(0.0113)	(0.0113)	(0.0114)	(0.0113)	(0.0114)
Cross-border deal	0.0019	0.0019	0.0027	0.0026	0.0023	0.0022
	(0.0108)	(0.0107)	(0.0108)	(0.0107)	(0.0108)	(0.0108)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6,580	6,580	6,580	6,580	6,580	6,580

Panel B: US-based target companies

DV: Realized deal	(1)	(2)	(3)	(4)	(5)	(6)
Dummy both alliance	0.0446***	0.0310**	0.0303**	0.0196	0.0370***	0.0257**
	(0.0121)	(0.0124)	(0.0128)	(0.0130)	(0.0125)	(0.0131)
Dummy direct alliance		0.3615***		0.3420***		0.3450***
		(0.0552)		(0.0584)		(0.0582)
Dummy indirect alliance			0.1317***	0.1126***		
			(0.0280)	(0.0305)		
Number indirect alliances					0.0435**	0.0360
					(0.0197)	(0.0254)
Private target	0.0167	0.0198	0.0211*	0.0231*	0.0201*	0.0220*
	(0.0119)	(0.0120)	(0.0121)	(0.0122)	(0.0121)	(0.0122)
Same state	0.1174***	0.1182***	0.1173***	0.1180***	0.1170***	0.1180***
	(0.0113)	(0.0113)	(0.0113)	(0.0113)	(0.0114)	(0.0113)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5,159	5,159	5,159	5,159	5,159	5,159

Table 4.3. *continued*

Panel C: Listed US-based target companies

DV: Realized deal	(1)	(2)	(3)	(4)	(5)	(6)
Dummy both alliance	0.0245	0.0089	0.0118	0.0018	0.0169	0.0065
	(0.0216)	(0.0216)	(0.0221)	(0.0219)	(0.0218)	(0.0216)
Dummy direct alliance		0.2327***		0.2159***		0.2180***
		(0.0463)		(0.0490)		(0.0499)
Dummy indirect alliance			0.0768**	0.0502		
			(0.0301)	(0.0330)		
Number indirect alliances					0.0236**	0.0111
					(0.0095)	(0.0119)
Same state	0.0519**	0.0532**	0.0540**	0.0545**	0.0522**	0.0533**
	(0.0262)	(0.0255)	(0.0262)	(0.0254)	(0.0262)	(0.0255)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,323	1,323	1,323	1,323	1,323	1,323

Legend: This table shows partial effects at the averages (PEA) of logistic regressions. The dependent variable is a dummy variable that equals one if a deal was realized, and zero otherwise. Panel A is a subsample that contains only acquirer companies from the biotechnology or pharmaceutical industry. Panel B restricts the subsample to US-based target companies. Panel C contains only listed US-based target companies. *Dummy both alliance* is a dummy variable that equals one if the acquirer and the target company had at least one strategic alliance (unrelated or related) prior to the M&A deal, and zero otherwise. *Dummy direct alliance* is a dummy variable that equals one if the acquirer and the target company had a direct strategic alliance prior to the M&A deal, and zero otherwise. *Dummy indirect alliance* is a dummy variable that equals one if the acquirer and the target company had an indirect strategic alliance prior to the M&A deal, and zero otherwise. *Number indirect alliances* counts the number of indirect alliances between the acquirer and the target company. *Private target* is a dummy variable that equals one if the target was a private company prior to the M&A deal, and zero otherwise. *Cross-border deal* is a dummy variable that equals one if the target was a non-US company, and zero otherwise. *Same state* is a dummy variable that equals one if the acquirer and the target company were in the same US-state, and zero otherwise. A constant is included in all regressions. Robust standard errors are displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.4. Probability of an M&A deal: estimations with interaction terms

	Panel A		**Panel B**		**Panel C**	
DV: Realized deal	(1)	(2)	(3)	(4)	(5)	(6)
Dummy both alliance	0.0101	0.0120	0.0180	0.0211	-0.0021	-0.0001
	(0.0122)	(0.0122)	(0.0134)	(0.0135)	(0.0212)	(0.0212)
Dummy direct alliance	0.6962***	0.6685***	0.6978***	0.6786***	0.5446***	0.4398***
	(0.0772)	(0.0726)	(0.0832)	(0.0782)	(0.1223)	(0.1051)
Dummy indirect alliance	0.1421***		0.1762***		0.0867**	
	(0.0451)		(0.0499)		(0.0424)	
Number indirect alliances		0.0742***		0.0857***		0.0389*
		(0.0262)		(0.0298)		(0.0205)
Dummy direct alliance x Dummy indirect alliance	-0.2218		-0.3345*		-0.3942**	
	(0.1768)		(0.1814)		(0.1822)	
Dummy direct alliance x Number indirect alliances		-0.0658**		-0.1141***		-0.0656
		(0.0289)		(0.0404)		(0.0400)
Private target	0.0168	0.0170	0.0229*	0.0230**		
	(0.0107)	(0.0107)	(0.0117)	(0.0117)		
Cross-border deal	0.0024	0.0022				
	(0.0107)	(0.0107)				
Same state			0.1488***	0.1491***	0.0582*	0.0609**
			(0.0173)	(0.0173)	(0.0309)	(0.0310)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6,580	6,580	5,159	5,159	1,323	1,323

Legend: This table shows results of OLS estimations. The dependent variable is a dummy variable that equals one if a deal was realized, and zero otherwise. Panel A is a subsample that contains only acquirer companies from the biotechnology or pharmaceutical industry. Panel B restricts the subsample to US-based target companies. Panel C contains only listed US-based target companies. *Dummy both alliance* is a dummy variable that equals one if the acquirer and the target company had at least one strategic alliance (unrelated or related) prior to the M&A deal, and zero otherwise. *Dummy direct alliance* is a dummy variable that equals one if the acquirer and the target company had a direct strategic alliance prior to the M&A deal, and zero otherwise. *Dummy indirect alliance* is a dummy variable that equals one if the acquirer and the target company had an indirect strategic alliance prior to the M&A deal, and zero otherwise. *Number indirect alliances* counts the number of indirect alliances between the acquirer and the target company. *Private target* is a dummy variable that equals one if the target was a private company prior to the M&A deal, and zero otherwise. *Cross-border deal* is a dummy variable that equals one if the target was a non-US company, and zero otherwise. *Same state* is a dummy variable that equals one if the acquirer and the target company were in the same US-state, and zero otherwise. A constant is included in all regressions. Robust standard errors are displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.5. Probability of an M&A deal: analysis with counterfactuals, distance

Subsample: US-based target companies (Panel B)

DV: Realized deal	(1)	(2)	(3)	(4)
Not same state	-0.1525***	-0.1487***	-0.1494***	-0.1496***
	(0.0194)	(0.0174)	(0.0175)	(0.0175)
Dummy both alliance	0.0352	0.0322**	0.0316**	0.0379***
	(0.0422)	(0.0134)	(0.0137)	(0.0138)
Dummy direct alliance		0.7204***		
		(0.0234)		
Dummy indirect alliance			0.1844	
			(0.1302)	
Number indirect alliances				0.0461**
				(0.0217)
Dummy both alliance x Not same state	0.0149			
	(0.0440)			
Dummy direct alliance x Not same state		-0.1042		
		(0.0907)		
Dummy indirect alliance x Not same state			0.0121	
			(0.1396)	
Number indirect alliances x Not same state				0.0271
				(0.0388)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	5,159	5,159	5,159	5,159

Legend: This table shows results of OLS estimations. The dependent variable is a dummy variable that equals one if a deal was realized, and zero otherwise. This sample contains only deals where the target company is US-based. *Not same state* is a dummy variable that equals one if the acquirer and target company were not in the same US-state. *Dummy both alliance* is a dummy variable that equals one if the acquirer and the target company had at least one strategic alliance (unrelated or related) prior to the M&A deal, and zero otherwise. *Dummy direct alliance* is a dummy variable that equals one if the acquirer and the target company had a direct strategic alliance prior to the M&A deal, and zero otherwise. *Dummy indirect alliance* is a dummy variable that equals one if the acquirer and the target company had an indirect strategic alliance prior to the M&A deal, and zero otherwise. *Number indirect alliances* counts the number of indirect alliances between the acquirer and the target company. Other control variables as well as a constant are included in all regressions. Robust standard errors are displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.6. Time to deal completion: Poisson estimations (QML)

DV: Time to completion	(1)	(2)	(3)	(4)
Dummy both alliance	0.2588**	0.2129**	0.1983**	0.2309**
	(0.1009)	(0.1011)	(0.1007)	(0.1011)
Dummy direct alliance	-0.4230			-0.6439***
	(0.2711)			(0.2477)
Dummy indirect alliance		0.0851		
		(0.1677)		
Number indirect alliances			0.0725***	0.1115***
			(0.0236)	(0.0306)
Public target	0.7001***	0.6979***	0.6866***	0.6852***
	(0.1078)	(0.1078)	(0.1083)	(0.1079)
Hostile takeover	0.4116	0.3606	0.3293	0.2953
	(0.4312)	(0.4536)	(0.4663)	(0.4934)
Cross-border deal	0.0005	0.0086	0.0121	0.0101
	(0.1234)	(0.1236)	(0.1237)	(0.1239)
Payment (mix)	0.2319	0.2536*	0.2296	0.1947
	(0.1535)	(0.1508)	(0.1532)	(0.1535)
Payment (stock)	0.5050***	0.5316***	0.5328***	0.4956***
	(0.1714)	(0.1692)	(0.1687)	(0.1699)
Payment (other)	-0.3478**	-0.3412**	-0.3458**	-0.3612**
	(0.1705)	(0.1714)	(0.1713)	(0.1709)
Divestiture	0.0081	0.0235	0.0316	0.0190
	(0.2097)	(0.2094)	(0.2098)	(0.2103)
Tender offer	-0.3391**	-0.3328**	-0.3208*	-0.3456**
	(0.1671)	(0.1674)	(0.1649)	(0.1678)
Unsolicited	0.2881	0.3008	0.2463	0.1867
	(0.4269)	(0.4330)	(0.4557)	(0.4767)
Rumor	0.4586**	0.4561**	0.4781**	0.4810**
	(0.1845)	(0.1884)	(0.1923)	(0.1932)
Year FE	Yes	Yes	Yes	Yes
N	816	816	816	816

Legend: This table shows results of a Poisson estimation. The dependent variable is non-negative and it counts the days between the announcement and completion date of an M&A deal. *Dummy both alliance* is a dummy variable that equals one if the acquirer and the target company had at least one strategic alliance (unrelated or related) prior to the M&A deal, and zero otherwise. *Dummy direct alliance* is a dummy variable that equals one if the acquirer and the target company had a direct strategic alliance prior to the M&A deal, and zero otherwise. *Dummy indirect alliance* is a dummy variable that equals one if the acquirer and the target company had an indirect strategic alliance prior to the M&A deal, and zero otherwise. *Number indirect alliances* counts the number of indirect alliances between the acquirer and the target company. *Public target* is a dummy variable that equals one if the target was a listed company prior to the M&A deal, and zero otherwise. *Cross-border deal* is a dummy variable that equals one if the target was a non-US company, and zero otherwise. *Same state* is a dummy variable that equals one if the acquirer and the target company were in the same US-state, and zero otherwise. *Payment (Mix)* is a dummy variable that equals one if the payment type is *mix*, and zero otherwise. *Payment (Stock)* is a dummy variable that equals one if the payment type is *stock*, and zero otherwise. *Payment (Other)* is a dummy variable that equals one if the payment type is *other*, and zero otherwise. *Hostile takeover* is a dummy variable that equals one if the deal is characterized as a hostile takeover, and zero otherwise. *Divestiture* is a dummy variable that equals one if the M&A deal was a divestiture sale, and zero otherwise. *Tender offer* is a dummy variable that equals one if the acquirer offers its stock in the M&A deal, and zero otherwise. *Unsolicited* is a dummy variable that equals one if the offer was unsolicited, and zero otherwise. *Rumor* is a dummy variable that equals one if the M&A deal started as a rumor, and zero otherwise. A constant is included in all regressions. Robust standard errors are displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.7. Time to deal completion: OLS estimations with interaction terms

DV: Time to completion	(1)	(2)	(3)	(4)
Dummy both alliance	0.8028***	0.6687***	0.8273***	0.7001***
	(0.1402)	(0.1478)	(0.1402)	(0.1475)
Dummy direct alliance	-0.8128		-0.9348*	
	(0.6103)		(0.5659)	
Dummy indirect alliance		1.5367***		-0.5331
		(0.3203)		(0.4649)
Dummy direct alliance x Public target	-0.8429			
	(0.9044)			
Dummy indirect alliance x Public target		-2.1419***		
		(0.4076)		
Dummy direct alliance x Payment (mix)			1.2367*	
			(0.6564)	
Dummy direct alliance x Payment (stock)			-4.1157***	
			(0.6449)	
Dummy direct alliance x Payment (other)			-0.8137	
			(1.0033)	
Dummy indirect alliance x Payment (mix)				0.9067*
				(0.5118)
Dummy indirect alliance x Payment (stock)				0.7046
				(0.5943)
Dummy indirect alliance x Payment (other)				-0.2763
				(1.3166)
Public target	1.5972***	1.6593***	1.5679***	1.5655***
	(0.1437)	(0.1471)	(0.1459)	(0.1513)
Payment (mix)	0.3130	0.3771*	0.3114	0.3382*
	(0.2007)	(0.2022)	(0.2009)	(0.2044)
Payment (stock)	0.4805**	0.5315***	0.5154***	0.5267***
	(0.1889)	(0.1917)	(0.1882)	(0.1952)
Payment (other)	-0.9953***	-0.9595***	-0.9694***	-0.9796***
	(0.1751)	(0.1776)	(0.1767)	(0.1781)
Controls	Yes	Yes	Yes	Yes
N	816	816	816	816

Legend: This table shows results of OLS estimations. The dependent variable is non-negative and it counts the days between the announcement and completion date of an M&A deal. *Dummy direct alliance* is a dummy variable that equals one if the acquirer and the target company had a direct strategic alliance prior to the M&A deal, and zero otherwise. *Dummy indirect alliance* is a dummy variable that equals one if the acquirer and the target company had an indirect strategic alliance prior to the M&A deal, and zero otherwise. *Number indirect alliances* counts the number of indirect alliances between the acquirer and the target company. *Public target* is a dummy variable that equals one if the target was a listed company prior to the M&A deal, and zero otherwise. *Payment (Mix)* is a dummy variable that equals one if the payment type is *mix*, and zero otherwise. *Payment (Stock)* is a dummy variable that equals one if the payment type is *stock*, and zero otherwise. *Payment (Other)* is a dummy variable that equals one if the payment type is *other*, and zero otherwise. A constant is included in all regressions. Robust standard errors are displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.8. Cash vs. stock payment: logit estimations

DV: Cash (0) vs. stock (1) payment	(1)	(2)	(3)	(4)
Dummy both alliance	0.0376	-0.0241	-0.0162	0.1741
	(0.0507)	(0.0536)	(0.0528)	(0.2640)
Dummy direct alliance	-0.2875***			-3.4488***
	(0.0287)			(1.1492)
Dummy indirect alliance		0.0506		
		(0.1197)		
Number indirect alliances			-0.0002	0.0633
			(0.0571)	(0.2868)
Public target	0.1124*	0.0941	0.0940	0.5426*
	(0.0624)	(0.0614)	(0.0613)	(0.2895)
Hostile takevoer	0.7327***	0.7208***	0.7210***	10.9815***
	(0.0240)	(0.0233)	(0.0234)	(1.1574)
Cross-border deal	-0.1762***	-0.1786***	-0.1795***	-1.0405***
	(0.0428)	(0.0438)	(0.0437)	(0.3071)
Divestiture	-0.2555***	-0.2567***	-0.2548***	-2.5907**
	(0.0403)	(0.0493)	(0.0498)	(1.1587)
Tender offer	-0.3360***	-0.3401***	-0.3393***	-3.5437***
	(0.0288)	(0.0295)	(0.0297)	(0.7359)
Unsolicited	-0.2991***	-0.3100***	-0.3098***	-10.6606***
	(0.0267)	(0.0258)	(0.0259)	(0.9692)
Rumor	-0.0942	-0.1094	-0.1130	-0.5278
	(0.0902)	(0.0998)	(0.0990)	(0.5919)
Year FE	Yes	Yes	Yes	Yes
N	545	545	545	545

Legend: This table shows partial effects at the averages (PEA) of logistic regressions. The dependent variable is a dummy variable that equals one if the type of payment in the M&A deal was stocks, and zero if the type of payment was cash. *Dummy both alliance* is a dummy variable that equals one if the acquirer and the target company had at least one strategic alliance (unrelated or related) prior to the M&A deal, and zero otherwise. *Dummy direct alliance* is a dummy variable that equals one if the acquirer and the target company had a direct strategic alliance prior to the M&A deal, and zero otherwise. *Dummy indirect alliance* is a dummy variable that equals one if the acquirer and the target company had an indirect strategic alliance prior to the M&A deal, and zero otherwise. *Number indirect alliances* counts the number of indirect alliances between the acquirer and the target company. *Public target* is a dummy variable that equals one if the target was a listed company prior to the M&A deal, and zero otherwise. *Hostile takeover* is a dummy variable that equals one if the deal is characterized as a hostile takeover, and zero otherwise. *Cross-border deal* is a dummy variable that equals one if the target was a non-US company, and zero otherwise. *Divestiture* is a dummy variable that equals one if the M&A deal was a divestiture sale, and zero otherwise. *Tender offer* is a dummy variable that equals one if the acquirer offers its stock in the M&A deal, and zero otherwise. *Unsolicited* is a dummy variable that equals one if the offer was unsolicited, and zero otherwise. *Rumor* is a dummy variable that equals one if the M&A deal started as a rumor, and zero otherwise. A constant is included in all regressions. Robust standard errors are displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.9. Post-M&A performance: OLS estimations

DV: $\Delta ROA_{(t+3)/(t-1)}$	(1)	(2)	(3)	(4)
Dummy both alliance	0.8497	0.8680	0.7938	0.7910
	(0.7449)	(0.7138)	(0.6994)	(0.7255)
Dummy direct alliance	0.2028			0.0262
	(1.3862)			(1.4640)
Dummy indirect alliance		0.0402		
		(1.0380)		
Number indirect alliances			0.2086	0.2074
			(0.2932)	(0.3162)
Public target	1.0072	1.0054	0.9588	0.9592
	(1.3247)	(1.3171)	(1.2894)	(1.2828)
Hostile takeover	-0.9751	-0.9985	-1.3186	-1.3170
	(1.9415)	(2.1420)	(1.9942)	(2.0218)
Cross-border deal	0.9454	0.9463	0.9512	0.9511
	(1.4066)	(1.4141)	(1.4120)	(1.4144)
Payment (mix)	-5.9675	-5.9770	-6.0333	-6.0319
	(5.0003)	(5.0031)	(5.0556)	(5.0831)
Payment (stock)	-0.4176	-0.4344	-0.4304	-0.4283
	(1.9780)	(1.9505)	(1.9602)	(1.9716)
Payment (other)	0.8593	0.8546	0.8292	0.8298
	(0.7566)	(0.7566)	(0.7488)	(0.7502)
Divestiture	1.2547	1.2497	1.2590	1.2598
	(1.4355)	(1.4486)	(1.4604)	(1.4561)
Tender offer	-0.5874	-0.5965	-0.5877	-0.5871
	(1.0867)	(1.0919)	(1.0786)	(1.0875)
Unsolicited	-0.8741	-0.9004	-1.0618	-1.0581
	(2.4945)	(2.5321)	(2.5888)	(2.6144)
Rumor	3.7680	3.7686	3.8274	3.8272
	(3.0226)	(3.0271)	(3.0694)	(3.0767)
Year FE	Yes	Yes	Yes	Yes
N	485	485	485	485

Legend: This table shows results of OLS estimations. The dependent variable is the difference between the return on assets (ROA) three years after and one year before the focal acquisition. *Dummy both alliance* is a dummy variable that equals one if the acquirer and the target company had at least one strategic alliance (unrelated or related) prior to the M&A deal, and zero otherwise. *Dummy direct alliance* is a dummy variable that equals one if the acquirer and the target company had a direct strategic alliance prior to the M&A deal, and zero otherwise. *Dummy indirect alliance* is a dummy variable that equals one if the acquirer and the target company had an indirect strategic alliance prior to the M&A deal, and zero otherwise. *Number indirect alliances* counts the number of indirect alliances between the acquirer and the target company. *Public target* is a dummy variable that equals one if the target was a listed company prior to the M&A deal, and zero otherwise. *Hostile takeover* is a dummy variable that equals one if the deal is characterized as a hostile takeover, and zero otherwise. *Cross-border deal* is a dummy variable that equals one if the target was a non-US company, and zero otherwise. *Payment (Mix)* is a dummy variable that equals one if the payment type is *mix*, and zero otherwise. *Payment (Stock)* is a dummy variable that equals one if the payment type is *stock*, and zero otherwise. *Payment (Other)* is a dummy variable that equals one if the payment type is *other*, and zero otherwise. *Divestiture* is a dummy variable that equals one if the M&A deal was a divestiture sale, and zero otherwise. *Tender offer* is a dummy variable that equals one if the acquirer offers its stock in the M&A deal, and zero otherwise. *Unsolicited* is a dummy variable that equals one if the offer was unsolicited, and zero otherwise. *Rumor* is a dummy variable that equals one if the M&A deal started as a rumor, and zero otherwise. A constant is included in all regressions. Robust standard errors are displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.10. Announcement returns: OLS estimations

	CAR[−2, +2]				CAR[−5, +5]			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dummy both alliance	-0.0070	-0.0144	-0.0100	-0.0089	-0.0032	-0.0068	-0.0052	-0.0058
	(0.0196)	(0.0128)	(0.0160)	(0.0181)	(0.0245)	(0.0167)	(0.0201)	(0.0226)
Dummy direct alliance	0.0012			-0.0109	0.0218			0.0052
	(0.0175)			(0.0247)	(0.0226)			(0.0288)
Dummy indirect alliance		0.0558				0.0462		
		(0.0656)				(0.0795)		
Number indirect alliances			0.0114	0.0120			0.0167	0.0164
			(0.0129)	(0.0137)			(0.0140)	(0.0152)
Public target	-0.0635***	-0.0649***	-0.0658***	-0.0659***	-0.0638***	-0.0648***	-0.0671***	-0.0671***
	(0.0183)	(0.0193)	(0.0200)	(0.0201)	(0.0225)	(0.0237)	(0.0244)	(0.0244)
Hostile takeover	-0.1213**	-0.1715**	-0.1532***	-0.1557***	-0.2513***	-0.2944***	-0.2997***	-0.2985***
	(0.0492)	(0.0695)	(0.0554)	(0.0580)	(0.0658)	(0.0884)	(0.0705)	(0.0741)
Cross-border deal	-0.0436***	-0.0417***	-0.0428***	-0.0428***	-0.0517***	-0.0503***	-0.0508***	-0.0507***
	(0.0113)	(0.0113)	(0.0113)	(0.0113)	(0.0148)	(0.0147)	(0.0147)	(0.0147)
Payment (mix)	-0.0115	-0.0114	-0.0133	-0.0140	0.0058	0.0049	0.0022	0.0025
	(0.0143)	(0.0143)	(0.0144)	(0.0147)	(0.0219)	(0.0217)	(0.0218)	(0.0222)
Payment (stock)	0.0130	0.0121	0.0131	0.0122	0.0266	0.0241	0.0250	0.0255
	(0.0233)	(0.0224)	(0.0230)	(0.0229)	(0.0279)	(0.0269)	(0.0275)	(0.0274)
Payment (other)	-0.0089	-0.0100	-0.0099	-0.0102	-0.0221	-0.0235	-0.0240	-0.0239
	(0.0114)	(0.0118)	(0.0117)	(0.0118)	(0.0146)	(0.0150)	(0.0149)	(0.0150)
Divestiture	-0.0333	-0.0306	-0.0336	-0.0335	0.0322	0.0346	0.0320	0.0319
	(0.0226)	(0.0247)	(0.0230)	(0.0232)	(0.0375)	(0.0390)	(0.0380)	(0.0380)
Tender offer	0.0088	0.0013	0.0079	0.0069	0.0143	0.0061	0.0111	0.0116
	(0.0186)	(0.0206)	(0.0182)	(0.0187)	(0.0219)	(0.0241)	(0.0216)	(0.0224)
Unsolicited	0.0331	0.0355	0.0358	0.0359	0.0969	0.0988*	0.1008*	0.1007*
	(0.0481)	(0.0473)	(0.0472)	(0.0473)	(0.0601)	(0.0592)	(0.0591)	(0.0591)
Rumor	0.0449*	0.0383	0.0468**	0.0471**	0.0313	0.0261	0.0344	0.0343
	(0.0241)	(0.0248)	(0.0238)	(0.0238)	(0.0281)	(0.0304)	(0.0284)	(0.0285)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	513	513	513	513	513	513	513	513

Legend: This table shows results of OLS estimations. The dependent variable for the estimations in columns 1 to 4 is the five-day cumulative abnormal return $(-2, +2)$. The dependent variable for the estimations in columns 5 to 8 is the eleven-day cumulative abnormal return $(-5, +5)$. *Dummy both alliance* is a dummy variable that equals one if the acquirer and the target company had at least one strategic alliance (unrelated or related) prior to the M&A deal, and zero otherwise. *Dummy direct alliance* is a dummy variable that equals one if the acquirer and the target company had a direct strategic alliance prior to the M&A deal, and zero otherwise. *Dummy indirect alliance* is a dummy variable that equals one if the acquirer and the target company had an indirect strategic alliance prior to the M&A deal, and zero otherwise. *Number indirect alliances* counts the number of indirect alliances between the acquirer and the target company. *Public target* is a dummy variable that equals one if the target was a listed company prior to the M&A deal, and zero otherwise. *Hostile takeover* is a dummy variable that equals one if the deal is characterized as a hostile takeover, and zero otherwise. *Cross-border deal* is a dummy variable that equals one if the target was a non-US company, and zero otherwise. *Payment (Mix)* is a dummy variable that equals one if the payment type is *mix*, and zero otherwise. *Payment (Stock)* is a dummy variable that equals one if the payment type is *stock*, and zero otherwise. *Payment (Other)* is a dummy variable that equals one if the payment type is *other*, and zero otherwise. *Divestiture* is a dummy variable that equals one if the M&A deal was a divestiture sale, and zero otherwise. *Tender offer* is a dummy variable that equals one if the acquirer offers its stock in the M&A deal, and zero otherwise. *Unsolicited* is a dummy variable that equals one if the offer was unsolicited, and zero otherwise. *Rumor* is a dummy variable that equals one if the M&A deal started as a rumor, and zero otherwise. A constant is included in all regressions. Robust standard errors are displayed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Chapter 5

General Conclusion

In addition to financial capital, VC firms also provide other useful resources. They add value to their portfolio companies by coaching, providing their expertise, and closely monitoring the activities of the entrepreneur. Ultimately, the VC firms aim to exit their investments either through an IPO or a trade sale. Such successful exits are important as the limited partners expect high returns on their investments. Toward this end, VC firms might have identified a new channel through which they can improve the likelihood of their portfolio company going public or being acquired. Strategic alliances are collaborations between two or more companies with a common goal. Such alliances have a positive effect on outsiders because a third party was willing to certify the quality of the portfolio company by entering a strategic alliance with them. On the one hand, these signals might have a positive effect on IPOs, as there are many uninformed investors at the time of the public offering. On the other hand, such alliances are unlikely to have a significant effect on M&As because there is thorough due diligence before an M&A, and the buyers have more information about the underlying company.

This dissertation contributes to the existing literature by analyzing the role of prior ties among VC investors, the effect of strategic alliances on IPOs and M&As, and the role of different types of related alliances before M&As.

For this purpose, Chapter 2 advances our knowledge of how networks between financial intermediaries contribute to a company's development. While existing studies demonstrate that alliances are more frequent among companies sharing

the same VC firm, this study provides evidence that strategic alliances are also more prevalent among companies indirectly connected through VC syndication networks. Furthermore, VC firms' ties mitigate asymmetric information problems that arise when alliances are formed. Connected VC firms are particularly beneficial when transaction and information costs are high. More specifically, positive connected-VC-effect increases when geographical and technological distances become more significant. Finally, this study provides empirical evidence that strategic alliances between companies from connected VC firms' portfolios tend to perform well, which is associated with higher IPO probabilities. This study documents a new channel through which portfolio companies benefit from ties among VC firms.

In light of the results in Chapter 2, this dissertation analyzes the role of strategic alliances in VC exits in Chapter 3. This work contributes to studies that highlight the distinctions between different exit routes. When companies go public, many potential buyers exist. A single buyer faces the free-riding problem, which reduces its incentive to collect information. In this situation, a potential uninformed buyer may interpret a strategic partnership as a certification of quality because another company was willing to form a strategic alliance with this particular company. However, before the acquisition, the single acquiring party will have incentives to conduct in-depth due diligence. By providing a methodological contribution, this study finds that strategic alliances have different effects for different types of exits. More specifically, there is empirical evidence for a positive effect of strategic alliances on IPOs, but not on M&As. Furthermore, the magnitude of the alliance effect is less than that reported in prior studies. Finally, the overall effect on M&As is insignificant. It is negative in the short-term and turns positive in the long-term.

The ambiguous results of the effect of alliances on M&As in Chapter 3 leads to the next research study. Chapter 4 focuses on different types of prior ties between the acquirer and target company in the context of an M&A. This study distinguishes between direct alliances and indirect alliances. Companies in an M&A are considered to have a direct tie if the acquirer and the target company entered into a strategic alliance. Indirect ties emerge when the acquirer and target company share a common strategic partner. Because of trust-building, access

to more information, and certification, companies with prior ties through related alliances are associated with a higher likelihood of a successful M&A. Prior ties in the form of related alliances reduce transaction costs, and thus, lead to a more efficient target selection and transaction process. The results also confirm a shorter transaction process if the acquirer and target company are connected through a related alliance. However, this study cannot confirm a significant effect of related alliances on post-M&A performance.

Overall, this dissertation provides extensive empirical analyses on the role of VC firms in the formation of strategic alliances and the role of strategic alliances in VC exits. It shows that VC firms play a more extended role in the formation of alliances than simply pairing their portfolio companies. Connected VC firms with an extensive history of syndication activities use their network to enhance partnerships among their own portfolio companies and the portfolio companies of their prior syndication partners. These alliances increase the probability of going public because strategic alliances serve as certification for third parties. However, in cases of M&As, the effect is not unambiguous. Prior ties through direct and indirect alliances among the acquirer and target company increase the probability of a successful M&A. These related alliances increase the efficiency of the target selection and transaction process. However, these alliances might affect post-M&A performance. Based on the results of this dissertation, future research studies could address the exact process that VC firms undertake to enhance strategic alliances, the reasons behind the choice between strategic alliances and M&As, and the efficient target selection.

References

Aakvik, A. (2001): "Bounding a matching estimator: The case of a Norwegian training program," *Oxford Bulletin of Economics and Statistics*, 63, 115–143.

Ahuja, G. (2000): "Collaboration networks, structural holes, and innovation: A longitudinal study," *Administrative Science Quarterly*, 45, 425–455.

Ai, C. and E. C. Norton (2003): "Interaction terms in logit and probit models," *Economics Letters*, 80, 123–129.

Allen, F. and G. R. Faulhaber (1989): "Signalling by underpricing in the IPO market," *Journal of Financial Economics*, 23, 303–323.

Anand, B. N. and T. Khanna (2000): "Do firms learn to create value? The case of alliances," *Strategic Management Journal*, 21, 295–315.

Aoki, M. (2000): "Information and governance in the Silicon Valley model," in *Corporate Governance: Theoretical and Empirical Perspectives*, ed. by X. Vives, Cambridge, UK: Cambridge University Press.

Barry, C. B., C. J. Muscarella, J. W. Peavy Iii, and M. R. Vetsuypens (1990): "The role of venture capital in the creation of public companies: Evidence from the going-public process," *Journal of Financial Economics*, 27, 447–471.

Basdeo, D. K., K. G. Smith, C. M. Grimm, V. P. Rindova, and P. J. Derfus (2006): "The impact of market actions on firm reputation," *Strategic Management Journal*, 27, 1205–1219.

Bauer, F. and K. Matzler (2014): "Antecedents of M&A success: The role of strategic complementarity, cultural fit, and degree and speed of integration," *Strategic Management Journal*, 35, 269–291.

Baum, J. A., T. Calabrese, and B. S. Silverman (2000): "Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology," *Strategic Management Journal*, 21, 267–294.

Berger, A. N. and G. F. Udell (1998): "The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle," *Journal of Banking & Finance*, 22, 613–673.

Bertoni, F. and T. Tykvová (2015): "Does governmental venture capital spur invention and innovation? Evidence from young European biotech companies," *Research Policy*, 44, 925–935.

Black, B. S. and R. J. Gilson (1998): "Venture capital and the structure of capital markets: Banks versus stock markets," *Journal of Financial Economics*, 47, 243–277.

Brander, J. A., R. Amit, and W. Antweiler (2002): "Venture-capital syndication: Improved venture selection vs. the value-added hypothesis," *Journal of Economics & Management Strategy*, 11, 423–452.

Burt, R. S. (2009): *Structural holes: The social structure of competition*, Harvard University Press.

Bushman, R. M., J. D. Piotroski, and A. J. Smith (2004): "What determines corporate transparency?" *Journal of Accounting Research*, 42, 207–252.

Cai, Y. and M. Sevilir (2012): "Board connections and M&A transactions," *Journal of Financial Economics*, 103, 327–349.

Caliendo, M. and S. Kopeinig (2008): "Some practical guidance for the implementation of propensity score matching," *Journal of Economic Surveys*, 22, 31–72.

Cameron, A. C. and P. K. Trivedi (2005): *Microeconometrics: Methods and applications*, Cambridge University Press.

Capron, L. and J.-C. Shen (2007): "Acquisitions of private vs. public firms: Private information, target selection, and acquirer returns," *Strategic Management Journal*, 28, 891–911.

Chakrabarti, A. and W. Mitchell (2013): "The persistent effect of geographic distance in acquisition target selection," *Organization Science*, 24, 1805–1826.

——— (2016): "The role of geographic distance in completing related acquisitions: Evidence from US. chemical manufacturers," *Strategic Management Journal*, 37, 673–694.

Chan, S. H., J. W. Kensinger, A. J. Keown, and J. D. Martin (1997): "Do strategic alliances create value?" *Journal of Financial Economics*, 46, 199–221.

Chang, S.-C. and M.-T. Tsai (2013): "The effect of prior alliance experience on acquisition performance," *Applied Economics*, 45, 765–773.

Chen, G., D. C. Hambrick, and T. G. Pollock (2008): "Puttin'on the Ritz: Pre-IPO enlistment of prestigious affiliates as deadline-induced remediation," *Academy of Management Journal*, 51, 954–975.

Cho, S. Y. and J. D. Arthurs (2018): "The influence of alliance experience on acquisition premiums and post-acquisition performance," *Journal of Business Research*, 88, 1–10.

Cohen, W. M. and D. A. Levinthal (1990): "Absorptive capacity: A new perspective on learning and innovation," *Administrative Science Quarterly*, 128–152.

Coval, J. D. and T. J. Moskowitz (1999): "Home bias at home: Local equity preference in domestic portfolios," *The Journal of Finance*, 54, 2045–2073.

Cumming, D. (2008): "Contracts and exits in venture capital finance," *Review of Financial Studies*, 21, 1947–1982.

Cumming, D., G. Fleming, and J.-A. Suchard (2005): "Venture capitalist value-added activities, fundraising and drawdowns," *Journal of Banking & Finance*, 29, 295–331.

Cumming, D. and S. Johan (2008): "Information asymmetries, agency costs and venture capital exit outcomes," *Venture Capital*, 10, 197–231.

Cumming, D. J. and J. G. MacIntosh (2003): "A cross-country comparison of full and partial venture capital exits," *Journal of Banking & Finance*, 27, 511–548.

Cuypers, I. R., Y. Cuypers, and X. Martin (2017): "When the target may know better: Effects of experience and information asymmetries on value from mergers and acquisitions," *Strategic Management Journal*, 38, 609–625.

Dai, N., H. Jo, and S. Kassicieh (2012): "Cross-border venture capital investments in Asia: Selection and exit performance," *Journal of Business Venturing*, 27, 666–684.

Daily, C. M., S. T. Certo, D. R. Dalton, and R. Roengpitya (2003): "IPO underpricing: A meta-analysis and research synthesis," *Entrepreneurship Theory and Practice*, 27, 271–295.

Das, S. R., H. Jo, and Y. Kim (2011): "Polishing diamonds in the rough: The sources of syndicated venture performance," *Journal of Financial Intermediation*, 20, 199–230.

Das, T. K. and B.-S. Teng (1999): "Managing risks in strategic alliances," *Academy of Management Perspectives*, 13, 50–62.

——— (2000): "Instabilities of strategic alliances: An internal tensions perspective," *Organization Science*, 11, 77–101.

——— (2001): "Trust, control, and risk in strategic alliances: An integrated framework," *Organization Studies*, 22, 251–283.

Deeds, D. L., D. Decarolis, and J. E. Coombs (1997): "The impact of firm-specific capabilities on the amount of capital raised in an initial public offering: Evidence from the biotechnology industry," *Journal of Business Venturing*, 12, 31–46.

Diestre, L. and N. Rajagopalan (2012): "Are all 'sharks' dangerous? New biotechnology ventures and partner selection in R&D alliances," *Strategic Management Journal*, 33, 1115–1134.

Dyer, J. H. and W. Chu (2003): "The role of trustworthiness in reducing transaction costs and improving performance: Empirical evidence from the United States, Japan, and Korea," *Organization Science*, 14, 57–68.

Fang, Y., D. Jin, X. Sun, and H. Wang (2015): "New evidence on alliance experience and acquisition performance: Short-run pain, long-run gain?" *Studies in Economics and Finance*, 32, 53–73.

Fine, J. P. and R. J. Gray (1999): "A proportional hazards model for the subdistribution of a competing risk," *Journal of the American Statistical Association*, 94, 496–509.

Fonti, F., M. Maoret, and R. Whitbred (2017): "Free-riding in multi-party alliances: The role of perceived alliance effectiveness and peers' collaboration in a research consortium," *Strategic Management Journal*, 38, 363–383.

Fried, V. H., G. D. Bruton, and R. D. Hisrich (1998): "Strategy and the board of directors in venture capital-backed firms," *Journal of Business Venturing*, 13, 493–503.

Giot, P. and A. Schwienbacher (2007): "IPOs, trade sales and liquidations: Modelling venture capital exits using survival analysis," *Journal of Banking & Finance*, 31, 679–702.

Gompers, P. and J. Lerner (2000): "Money chasing deals? The impact of fund inflows on private equity valuation," *Journal of Financial Economics*, 55, 281–325.

Gompers, P. A. (1995): "Optimal investment, monitoring, and the staging of venture capital," *The Journal of Finance*, 50, 1461–1489.

Gompers, P. A. and J. Lerner (2004): *The venture capital cycle*, MIT press.

Gorman, M. and W. A. Sahlman (1989): "What do venture capitalists do?" *Journal of Business Venturing*, 4, 231–248.

Grilli, L. and S. Murtinu (2014): "Government, venture capital and the growth of European high-tech entrepreneurial firms," *Research Policy*, 43, 1523–1543.

Gulati, R. (1995a): "Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances," *Academy of Management Journal*, 38, 85–112.

——— (1995b): "Social structure and alliance formation patterns: A longitudinal analysis," *Administrative Science Quarterly*, 619–652.

——— (1998): "Alliances and networks," *Strategic Management Journal*, 19, 293–317.

——— (1999): "Network location and learning: The influence of network resources and firm capabilities on alliance formation," *Strategic Management Journal*, 20, 397–420.

Gulati, R., D. Lavie, and H. Singh (2009): "The nature of partnering experience and the gains from alliances," *Strategic Management Journal*, 30, 1213–1233.

Gulati, R. and H. Singh (1998): "The architecture of cooperation: Managing coordination costs and appropriation concerns in strategic alliances," *Administrative Science Quarterly*, 781–814.

Hagedoorn, J. and B. Sadowski (1999): "The transition from strategic technology alliances to mergers and acquisitions: An exploratory study," *Journal of Management Studies*, 36, 87–107.

Hamel, G., Y. L. Doz, and C. K. Prahalad (1989): "Collaborate with your competitors and win," *Harvard Business Review*, 67, 133–139.

Hamilton, B. H. and J. A. Nickerson (2003): "Correcting for endogeneity in strategic management research," *Strategic Organization*, 1, 51–78.

Harford, J., R. Schonlau, and J. Stanfield (2019): "Trade relationships, indirect economic links, and mergers," *Management Science*, 65, 3085–3110.

He, Z., H. Yu, and L. Du (2018): "Cohabitation before marriage: do prior alliances enhance post-merger performance?" *Review of Quantitative Finance and Accounting*, 1–35.

Healy, P. M., K. G. Palepu, and R. S. Ruback (1992): "Does corporate performance improve after mergers?" *Journal of Financial Economics*, 31, 135–175.

Hellmann, T. and M. Puri (2000): "The interaction between product market and financing strategy: The role of venture capital," *The Review of Financial Studies*, 13, 959–984.

——— (2002): "Venture capital and the professionalization of start-up firms: Empirical evidence," *The Journal of Finance*, 57, 169–197.

Higgins, M. J. and D. Rodriguez (2006): "The outsourcing of R&D through acquisitions in the pharmaceutical industry," *Journal of Financial Economics*, 80, 351–383.

Hochberg, Y. V. (2012): "Venture capital and corporate governance in the newly public firm," *Review of Finance*, 16, 429–480.

Hochberg, Y. V., A. Ljungqvist, and Y. Lu (2007): "Whom you know matters: Venture capital networks and investment performance," *The Journal of Finance*, 62, 251–301.

——— (2010): "Networking as a barrier to entry and the competitive supply of venture capital," *The Journal of Finance*, 65, 829–859.

Hoenig, D. and J. Henkel (2015): "Quality signals? The role of patents, alliances, and team experience in venture capital financing," *Research Policy*, 44, 1049–1064.

Hsu, D. H. (2004): "What do entrepreneurs pay for venture capital affiliation?" *The Journal of Finance*, 59, 1805–1844.

Kaplan, S. N. and P. Strömberg (2001): "Venture capitals as principals: Contracting, screening, and monitoring," *American Economic Review*, 91, 426–430.

——— (2003): "Financial contracting theory meets the real world: An empirical analysis of venture capital contracts," *The Review of Economic Studies*, 70, 281–315.

Kaplan, S. N. and P. E. Strömberg (2004): "Characteristics, contracts, and actions: Evidence from venture capitalist analyses," *The Journal of Finance*, 59, 2177–2210.

Khoury, T. A., M. Junkunc, and D. L. Deeds (2013): "The social construction of legitimacy through signaling social capital: Exploring the conditional value of alliances and underwriters at IPO," *Entrepreneurship Theory and Practice*, 37, 569–601.

King, D. R., D. R. Dalton, C. M. Daily, and J. G. Covin (2004): "Meta-analyses of post-acquisition performance: Indications of unidentified moderators," *Strategic Management Journal*, 25, 187–200.

Koka, B. R. and J. E. Prescott (2002): "Strategic alliances as social capital: A multidimensional view," *Strategic Management Journal*, 23, 795–816.

Kortum, S. and J. Lerner (2000): "Assessing the contribution of venture capital to innovation," *RAND Journal of Economics*, 31, 674–692.

Lee, P. M. and S. Wahal (2004): "Grandstanding, certification and the underpricing of venture capital backed IPOs," *Journal of Financial Economics*, 73, 375–407.

Lerner, J. (1994): "Venture capitalists and the decision to go public," *Journal of Financial Economics*, 35, 293–316.

——— (1995): "Venture capitalists and the oversight of private firms," *The Journal of Finance*, 50, 301–318.

Lindsey, L. (2008): "Blurring firm boundaries: The role of venture capital in strategic alliances," *The Journal of Finance*, 63, 1137–1168.

Mantel, N. and W. Haenszel (1959): "Statistical aspects of the analysis of data from retrospective studies of disease," *Journal of the National Cancer Institute*, 22, 719–748.

Megginson, W. L. and K. A. Weiss (1991): "Venture capitalist certification in initial public offerings," *The Journal of Finance*, 46, 879–903.

Milgrom, P. and J. Roberts (1986): "Price and advertising signals of product quality," *Journal of Political Economy*, 94, 796–821.

Mitchell, W. and K. Singh (1996): "Survival of businesses using collaborative relationships to commercialize complex goods," *Strategic Management Journal*, 17, 169–195.

Nahata, R. (2008): "Venture capital reputation and investment performance," *Journal of Financial Economics*, 90, 127–151.

Nahata, R., S. Hazarika, and K. Tandon (2014): "Success in global venture capital investing: Do institutional and cultural differences matter?" *Journal of Financial and Quantitative Analysis*, 49, 1039–1070.

Owen, S. and A. Yawson (2013): "Information asymmetry and international strategic alliances," *Journal of Banking & Finance*, 37, 3890–3903.

Ozmel, U., J. J. Reuer, and R. Gulati (2013a): "Signals across multiple networks: How venture capital and alliance networks affect interorganizational collaboration," *Academy of Management Journal*, 56, 852–866.

Ozmel, U., D. T. Robinson, and T. E. Stuart (2013b): "Strategic alliances, venture capital, and exit decisions in early stage high-tech firms," *Journal of Financial Economics*, 107, 655–670.

Payne, G. T., C. B. Moore, S. E. Griffis, and C. W. Autry (2011): "Multilevel challenges and opportunities in social capital research," *Journal of Management*, 37, 491–520.

Pisano, G. P. (1994): "Knowledge, integration, and the locus of learning: An empirical analysis of process development," *Strategic Management Journal*, 15, 85–100.

Plummer, L. A., T. H. Allison, and B. L. Connelly (2016): "Better together? Signaling interactions in new venture pursuit of initial external capital," *Academy of Management Journal*, 59, 1585–1604.

Popov, A. and P. Roosenboom (2012): "Venture capital and patented innovation: Evidence from Europe," *Economic Policy*, 27, 447–482.

Porrini, P. (2004): "Alliance experience and value creation in high-tech and low-tech acquisitions," *The Journal of High Technology Management Research*, 15, 267–292.

Qi, J., N. K. Sutton, and Q. Zheng (2015): "The value of strategic alliances in acquisitions and IPOs," *Financial Management*, 44, 387–430.

Raub, W. and J. Weesie (1990): "Reputation and efficiency in social interactions: An example of network effects," *American Journal of Sociology*, 96, 626–654.

Reuer, J. J. and R. Ragozzino (2008): "Adverse selection and M&A design: The roles of alliances and IPOs," *Journal of Economic Behavior & Organization*, 66, 195–212.

Reuer, J. J., M. Zollo, and H. Singh (2002): "Post-formation dynamics in strategic alliances," *Strategic Management Journal*, 23, 135–151.

Robinson, D. T. and T. E. Stuart (2007a): "Financial contracting in biotech strategic alliances," *Journal of Law and Economics*, 50, 559–596.

——— (2007b): "Network effects in the governance of strategic alliances," *Journal of Law, Economics, and Organization*, 23, 242–273.

Rosenbaum, P. R. (2002): *Observational studies*, Springer.

Rosenbaum, P. R. and D. B. Rubin (1983): "The central role of the propensity score in observational studies for causal effects," *Biometrika*, 70, 41–55.

——— (1985): "Constructing a control group using multivariate matched sampling methods that incorporate the propensity score," *The American Statistician*, 39, 33–38.

Rothaermel, F. T. (2001a): "Complementary assets, strategic alliances, and the incumbent's advantage: An empirical study of industry and firm effects in the biopharmaceutical industry," *Research Policy*, 30, 1235–1251.

——— (2001b): "Incumbent's advantage through exploiting complementary assets via interfirm cooperation," *Strategic Management Journal*, 22, 687–699.

Rothaermel, F. T. and D. L. Deeds (2004): "Exploration and exploitation alliances in biotechnology: A system of new product development," *Strategic Management Journal*, 25, 201–221.

Sadowski, B. and G. Duysters (2008): "Strategic technology alliance termination: An empirical investigation," *Journal of Engineering and Technology Management*, 25, 305–320.

Sahlman, W. A. (1990): "The structure and governance of venture-capital organizations," *Journal of Financial Economics*, 27, 473–521.

Shan, W., G. Walker, and B. Kogut (1994): "Interfirm cooperation and startup innovation in the biotechnology industry," *Strategic Management Journal*, 15, 387–394.

Singh, J. (2008): "Distributed R&D, cross-regional knowledge integration and quality of innovative output," *Research Policy*, 37, 77–96.

Singh, K. and W. Mitchell (2005): "Growth dynamics: The bidirectional relationship between interfirm collaboration and business sales in entrant and incumbent alliances," *Strategic Management Journal*, 26, 497–521.

Sørensen, M. (2007): "How smart is smart money? A two-sided matching model of venture capital," *The Journal of Finance*, 62, 2725–2762.

Sorenson, O. and T. E. Stuart (2001): "Syndication networks and the spatial distribution of venture capital investments," *American Journal of Sociology*, 106, 1546–1588.

Spence, M. (1973): "Job market signaling," *The Quarterly Journal of Economics*, 87, 355–374.

Stuart, T. E. (1998): "Network positions and propensities to collaborate: An investigation of strategic alliance formation in a high-technology industry," *Administrative Science Quarterly*, 43, 668–698.

——— (2000): "Interorganizational alliances and the performance of firms: A study of growth and innovation rates in a high-technology industry," *Strategic Management Journal*, 21, 791–811.

Stuart, T. E., H. Hoang, and R. C. Hybels (1999): "Interorganizational endorsements and the performance of entrepreneurial ventures," *Administrative Science Quarterly*, 44, 315–349.

Tian, X. (2012): "The role of venture capital syndication in value creation for entrepreneurial firms," *Review of Finance*, 16, 245–283.

Tykvová, T. (2018): "Venture capital and private equity financing: An overview of recent literature and an agenda for future research," *Journal of Business Economics*, 88, 325–362.

Tykvová, T. and A. Schertler (2014): "Does syndication with local venture capitalists moderate the effects of geographical and institutional distance?" *Journal of International Management*, 20, 406–420.

Uzzi, B. (1996): "The sources and consequences of embeddedness for the economic performance of organizations: The network effect," *American Sociological Review*, 674–698.

Villalonga, B. and A. M. McGahan (2005): "The choice among acquisitions, alliances, and divestitures," *Strategic Management Journal*, 26, 1183–1208.

Walker, G., B. Kogut, and W. Shan (1997): "Social capital, structural holes and the formation of an industry network," *Organization Science*, 8, 109–125.

Wang, H., R. J. Wuebker, S. Han, and M. D. Ensley (2012): "Strategic alliances by venture capital backed firms: An empirical examination," *Small Business Economics*, 38, 179–196.

Welch, I. (1989): "Seasoned offerings, imitation costs, and the underpricing of initial public offerings," *The Journal of Finance*, 44, 421–449.

White, S. and S. Siu-Yun Lui (2005): "Distinguishing costs of cooperation and control in alliances," *Strategic Management Journal*, 26, 913–932.

Williams, R. (2009): "Using heterogeneous choice models to compare logit and probit coefficients across groups," *Sociological Methods & Research*, 37, 531–559.

Winton, A. and V. Yerramilli (2008): "Entrepreneurial finance: Banks versus venture capital," *Journal of Financial Economics*, 88, 51–79.

Wooldridge, J. M. (2010): *Econometric analysis of cross section and panel data*, MIT press.

Yang, H., Z. Lin, and M. W. Peng (2011): "Behind acquisitions of alliance partners: Exploratory learning and network embeddedness," *Academy of Management Journal*, 54, 1069–1080.

Yang, H., Y. Zheng, and X. Zhao (2014): "Exploration or exploitation? Small firms' alliance strategies with large firms," *Strategic Management Journal*, 35, 146–157.

Yang, T. and H. E. Aldrich (2012): "Out of sight but not out of mind: Why failure to account for left truncation biases research on failure rates," *Journal of Business Venturing*, 27, 477–492.

Zaheer, A. and G. G. Bell (2005): "Benefiting from network position: firm capabilities, structural holes, and performance," *Strategic Management Journal*, 26, 809–825.

Zaheer, A., E. Hernandez, and S. Banerjee (2010): "Prior alliances with targets and acquisition performance in knowledge-intensive industries," *Organization Science*, 21, 1072–1091.

Zollo, M. and J. J. Reuer (2010): "Experience spillovers across corporate development activities," *Organization Science*, 21, 1195–1212.

UNIVERSITÄT HOHENHEIM

KO-AUTORENERKLÄRUNG *DECLARATION OF CO-AUTHORSHIP*

(Für kumulative Dissertationen)

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

Leonhard Brinster

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

The Role of Strategic Alliances in VC Exits: Evidence from the Biotechnology Industry

☐ nicht eingereicht (*not submitted*)

■ eingereicht bei (*submitted to*):

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

Venture Capital-An International Journal of Entrepreneurial 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. Christian Hopp, RWTH Aachen University, Chair of Technology Entrepreneurship, Kackertstr. 7, 52072 Aachen, Germany, Phone: +49-241-80 96676, e-mail: christian.hopp@rwth-aachen.de.
2. Tereza Tykvová, University of Hohenheim, Chair of Corporate Finance, Wollgrasweg 49, 70599 Stuttgart, Germany, Phone: +49-711-459 24501, e-mail: tereza.tykvova@uni-hohenheim.de.
3.
4.

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

Stuttgart, 07.01.2020

Ort, Datum *Place, Date*

Unterschrift Ko-Autor *Signature Co-author*

UNIVERSITÄT HOHENHEIM

KO-AUTORENERKLÄRUNG *DECLARATION OF CO-AUTHORSHIP*

(Für kumulative Dissertationen)

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

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

The Role of Strategic Alliances in VC Exits: Evidence from the Biotechnology Industry

- ☐ nicht eingereicht (*not submitted*)
- ■ eingereicht bei (*submitted to*):
- ☐ Zur Veröffentlichung angenommen oder veröffentlicht in (*accepted for publication or published in*):

Venture Capital-An International Journal of Entrepreneurial 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. Christian Hopp, RWTH Aachen University, Chair of Technology Entrepreneurship, Kackertstr. 7, 52072 Aachen, Germany, Phone: +49-241-80 96676, e-mail: christian.hopp@rwth-aachen.de.
2. Tereza Tykvová, University of St.Gallen, Chair of Private Markets and Alternative Investments, Unterer Graben 21, 9000 St. Gallen, Switzerland, Phone: +41-71-224-7032, em-mail: tereza.tykvova@unisg.ch.
3.
4.

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

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

5.3.20, St Gallen

Ort, Datum *Place, Date*

Unterschrift Ko-Autor *Signature Co-author*

UNIVERSITÄT HOHENHEIM

KO-AUTORENERKLÄRUNG *DECLARATION OF CO-AUTHORSHIP*

(Für kumulative Dissertationen)

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

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

Connected VCs and Strategic Alliances

☐ nicht eingereicht (*not submitted*)

■ eingereicht bei (*submitted to*):

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

Journal 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. Tereza Tykvová, University of St.Gallen, Chair of Private Markets and Alternative Investments, Unterer Graben 21, 9000 St. Gallen, Switzerland, Phone: +41-71-224-7032, em-mail: tereza.tykvova@unisg.ch.
2.
3.
4.

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

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

St. Gallen, 5.3.20

Ort, Datum *Place, Date*

Unterschrift Ko-Autor *Signature Co-author*