The Role of VC Syndication Ties in Formation of Strategic Alliances[*]

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Abstract

Prior research suggests that venture capital investors (VCs) are beneficial to alliance formation because they have insights into their portfolio companies' needs, facilitate access towards potential partners and certify their companies' quality towards these partners. Moreover, if two companies are backed by the same VC, these effects reinforce. Consequently, same-VC-backed companies close more often an alliance with each other than companies that do not share a common VC. We expect to observe such reinforcing effect also within a broader VC syndication network. By analyzing strategic alliances of venture-backed biotechnology companies, we find that prior ties between VCs significantly improve access to potential strategic alliance partners. This "same VC syndication network" effect even outweighs the "same VC" effect. Our results also lend support to the conclusion that alliances between companies of connected VCs improve companies' IPO chances.

JEL *classification:* G24, L24, L26

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1 Introduction

Venture capital investors (VCs) are financial intermediaries that offer funds to high-growth companies. Furthermore, they provide non-monetary value-added services, such as coaching or mentoring. In addition, they improve access to “third parties”, such as further investors, human capital, suppliers, customers, public institutions, industry associations or strategic alliance partners (e.g., Sahlman 1990). In this study, we focus on VC’s role in the formation of strategic alliances. Strategic alliances are beneficial to portfolio companies. They may be an important source of value for young companies because they connect them with other companies that have complementary resources (Pisano 1994; Shan et al. 1994; Mitchell and Singh 1996; Stuart 2000; Singh and Mitchell 2005). These connections may improve companies’ prospects, help them to grow and reach their goals (e.g., Ozmel et al. 2013a).

From existing literature, we already know that VCs increase the alliance activity in their companies (e.g., Ozmel et al. 2013b). Additionally, previous literature showed that two VC-backed companies that obtain funding from the same VC more often close an alliance than companies that were financed by two different VCs (Lindsey 2008) and that a bigger syndication investment, i.e. the number of involved investors, is related to a higher number of strategic alliances (Wang et al. 2012). We aim to answer the question whether and how portfolio companies benefit from VC syndication networks. Not only should a common VC investor increase the chances that two of her portfolio companies engage in a strategic alliance vis-à-vis two companies from portfolios of two different VCs, but we also expect that companies backed by two different VCs have a higher likelihood to close an alliance if these VCs know each other from prior joint investments. Moreover, we assume that this likelihood increases with the number of prior joint investments.

To answer this question, we rely on a dataset of 683 strategic alliances formed between 2004 and 2016 of 202 US VC-backed biotech companies. We rely on a cohort of all VC-backed biotech companies founded between 2004 and 2008. We collect information about their VC financing rounds and about all their strategic alliances. For the alliance partners, we also extract data on all their VC financing rounds. In 295 cases (43.2%), both the biotech company and the alliance partner are VC-backed. In the remaining 388 cases (56.8%), only the biotech is VC-backed.

Despite their popularity and the acclaimed benefits (e.g., Chan et al. 1997 or Das et al. 1998), many strategic alliances fail to meet expectations. There are several reasons for which strategic alliances appear to be a fragile construct. At the very beginning, it is costly to find an appropriate partner. Moreover, the partner selection process is a subject to information asymmetries since the partner quality is unknown to the other party. After an alliance formation, both parties may be exposed to moral hazard because the joint involvement in a business generates incentives to free ride on the information acquisition and effort of the other party. Additionally, expropriation risks might play a significant role when deciding if and with which partner to collaborate because the information leakage towards the partner, a potential competitor, is pertinent.

All these problems are particularly pronounced in young biotech companies. In the first years of their existence, these companies typically do not have enough experience to identify beneficial business combinations and appropriate collaboration partners. They typically do not enjoy large networks they could tap to find these partners. Consequently, they usually face larger transaction and adverse selection costs than established companies or companies from traditional sectors. As young biotech companies develop new potentially highly valuable products, they also face expropriation risks.

In addition, young biotech companies usually do not have tangible but rather intangible assets and the uncertainty regarding their future outcomes is substantial. The reduction in asymmetric information, moral hazard and expropriation risks could be achieved through screening and monitoring the counterparty. However, the ex-ante quality and ex-post actions of the counterparty are hard and costly to observe so that screening and monitoring will prohibitively increase the costs of cooperation on both sides. Under these circumstances, it seems to be challenging for young biotech companies to find appropriate and reliable strategic partners who are willing to invest.

When parties find it costly to accurately evaluate the quality of resources that partners can bring to the table, the existence of informed active investors and the certification through these investors can be valuable in overcoming the problems that arise from asymmetric information. In this environment, VC network may provide several benefits and help to mitigate the problems mentioned above. VCs, as active investors, have access to detailed information about the companies they finance and they know their portfolio companies' needs. This knowledge may be helpful in finding appropriate partners (Aoki 2000). Consequently, they may launch beneficial business combinations within their own and their network partners' (existing and prior) portfolios and mitigate problems stemming from asymmetric information as well as transaction costs associated to partner search.

Because VCs beneficially interact with other VCs from their network repeatedly, they want to maintain their good reputation within the network. VCs are interested in further collaborations and therefore, they avoid undesirable behavior towards other VCs in their network. Otherwise, they must fear that other VCs in their network will withhold them from any future beneficial cooperations. In addition, VCs want to attract high-quality promising deals. However, high-quality entrepreneurs tend to match with high-quality partners (Sørensen 2007). Consequently, when a VC gains reputation as a reliable partner who is associated with beneficial business combinations, it is more likely that this VC will attract better deals and obtain a better position within her VC network. Therefore, VCs from the own network are well-suited as a certification device (Hochberg et al. 2007; 2010) and companies inside the VC network should enjoy more trust than companies outside the network. In turn, adverse selection costs and uncertainties will be reduced. Also, the network VC may limit misconduct and protect the partner from moral hazard and expropriation risks. When they still hold strong control rights, they may discipline the management of the companies and avoid expropriation of one company by the other company.

This research contributes to four main strands of literature. First, we add to the literature that deals with the relation between VC financing and strategic alliance activity. This topic has attracted some attention since the seminal study of Lindsey (2008). In her study, Lindsey (2008) finds that strategic alliances are more common among companies that were financed by the same VC. The author does not consider the influence of previous connections between VCs. We extend her analysis by shedding light on whether prior ties between VCs affect cooperation patterns of VC-backed companies, and whether VC-backed companies are more likely to engage in cooperation with companies, in which a connected VC invests. We expect to observe positive effects of VC financing on alliance formation not only within a solo-VC existing and prior portfolios, but also between portfolios of VCs that share a joint network. In a similar way as VCs share access to deals at the very beginning within their networks (Tian 2012), they may later share access to potential cooperation partners to their portfolio companies. Our results support this view and show that the effect of prior ties is at least as important as the same VC effect.

Second, we add to the literature that focuses on the effect of VC syndication and VC networks. Recent theoretical and empirical work studies the involvement of a partner VC as a common means to access new financial and managerial resources. Prior research suggests that

VCs and portfolio companies benefit from this networking. In essence, sharing deal-flow and creating value-added through partner involvement creates benefits beyond the solo-VC and may well reside within the wider network context. Hochberg et al. (2007) analyze the performance consequences of syndicate relationships formed in the US venture capital industry and show that investee companies whose investors endue a more influential position within the VC network perform substantially better. They argue that VCs who are more open to syndication also enjoy more favorable network positions that enable them to benefit from high-quality relationships. As such, the syndication of VC investments affects the main drivers of performance: sourcing high-quality deals and promoting growth and innovations for the investee companies (e.g., Bertoni and Tykvová 2015). Lerner (1994) suggests that the evaluation of the same venture proposal by different VCs operating in a syndicate reduces the potential danger of adverse selection. Brander et al. (2002) see the VC market as a pool of productive resources in which a VC can access resources from another VC through syndication. The benefit of involving co-investors is derived from heterogeneous skills and information sets where different VCs contribute to the management of the portfolio company. We are the first to analyze whether portfolio companies directly benefit from the VC syndication networks via improving contacts to potential cooperation partners from network VCs' portfolios. Ozmel et al. (2013b) mention that prominent networks may help portfolio companies to find appropriate partners. However, they do not delve into the identity of the network collaborations and strategic partners, but rather demonstrate that networks in general are positively associated with alliance formation. We extend these findings by looking at the entire VC financing history of both alliance partners. By tracing the VCs' prior ties on both sides of the alliance, we are able to look for overlaps and their effects on alliance formation.

Third, we contribute to the more general literature on VC value-added. Many 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, administrative issues or marketing activities (see, e.g., Sapienza 1992; Hellmann and Puri 2002; Kaplan and Strömberg 2004; Cumming et al. 2005; Hochberg et al. 2007; Hochberg 2012). While many studies demonstrate value creation in VC-backed companies[1], only a few studies focus on the concrete areas

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

of involvement in more detail. Our paper contributes to filling this gap by shedding light on one of the areas, in which VCs become active, namely the strategic alliance formation.

We finally add to the vast management and organization literature that considers effects that prior ties may have on company actions and strategies. Gulati (1998; 1999) finds out that such networks are related to alliance formation. Networks may serve as a governance mechanism for inter-company connections (e.g., Robinson and Stuart 2007). Singh (2008) reports that social networks are important predictors of intraregional and intracompany knowledge flows. We complement this literature by focusing on prior ties between VCs and their effects on networking among portfolio companies in form of alliance formation.

The remainder of the paper is structured as follows. The next section presents our dataset and provides descriptive statistics of the VC-backed biotech companies and their strategic alliances. Section 3 describes the methodology we use to construct the sample of counterfactual alliances. It also provides descriptive statistics related to realized and counterfactual alliances. Section 4 shows the results of our main multivariate analyses that deal with the likelihood that a biotech company forms a strategic alliance with a particular partner. Section 5 deals with alternative ways of creating the counterfactual alliances samples and with extensions to IPO exits. Section 6 concludes.

2 VC-backed biotech companies and their strategic alliances

We consider strategic alliances of young US VC-backed biotechnology companies. The databases Dow Jones VentureSource and Thomson One VentureXpert provide us with the necessary information about all VC-backed biotechnology companies that were founded between 2004 and 2008. We rely on a cohort of companies of a similar age that all belong to one industry to reduce concerns of unobserved heterogeneity due to different development stages of the companies and 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), patenting (Patstat), company characteristics (S&P Capital IQ) and exit (Dow Jones VentureSource and Thomson One VentureXpert) until 2016. After excluding companies which did not disclose the VC investors and after elimination of duplicate entries, we end up with 738 companies. We then extract data on their alliance activity between 2004 and 2016 from S&P Capital IQ. Finally, we end up with 683

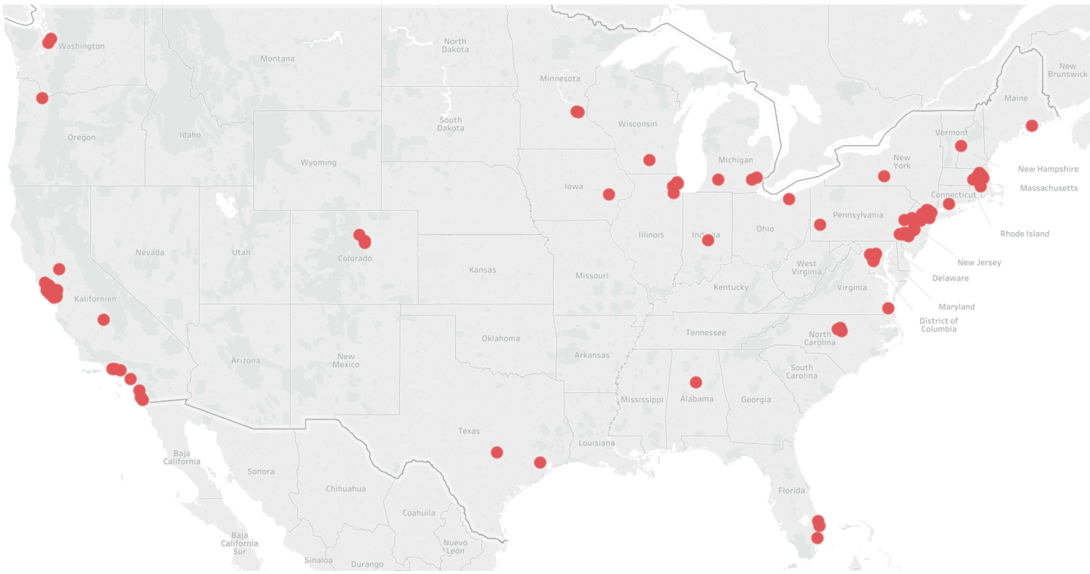

Figure 1. Geographical location of biotech companies

strategic alliances by 202 companies.

Figure 1 displays the geographical location of these sample companies. We observe clustering in a few US states, such as California, Massachusetts or New Jersey.

Table 1, Panel A shows descriptive statistics of the biotech companies. It reveals that at the time of the first alliance, the sample 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 biotech company has applied for 7.03 patents, the median number of patent applications is 3 and a few companies have already a large number of patent applications (the maximum number is 147). The companies have on average obtained financing from 4.4 different investors, with a fraction of 32% non-US investors. The involved VCs have on average invested in 67 rounds prior to their first investment in the biotech company and they have on average ties to 255 prior syndication partners. 24% of the biotech companies from our sample reach an IPO exit.

Figure 2 depicts the distribution of realized strategic alliances by years. Older companies realize more strategic alliances. However, in our sample the frequency of realized alliances does not grow constantly. From 2011 to 2013 the yearly number of newly formed alliances decreased before showing a peak in 2016.

Next, we turn to the strategic alliance partners of our VC-backed US-based biotech companies. Figure 3 displays the geographical location of the partner companies. Approximately 35% of all partners are located outside the US, mostly in Western Europe.

There are 497 unique strategic alliances partners. For all these partners, we extract data

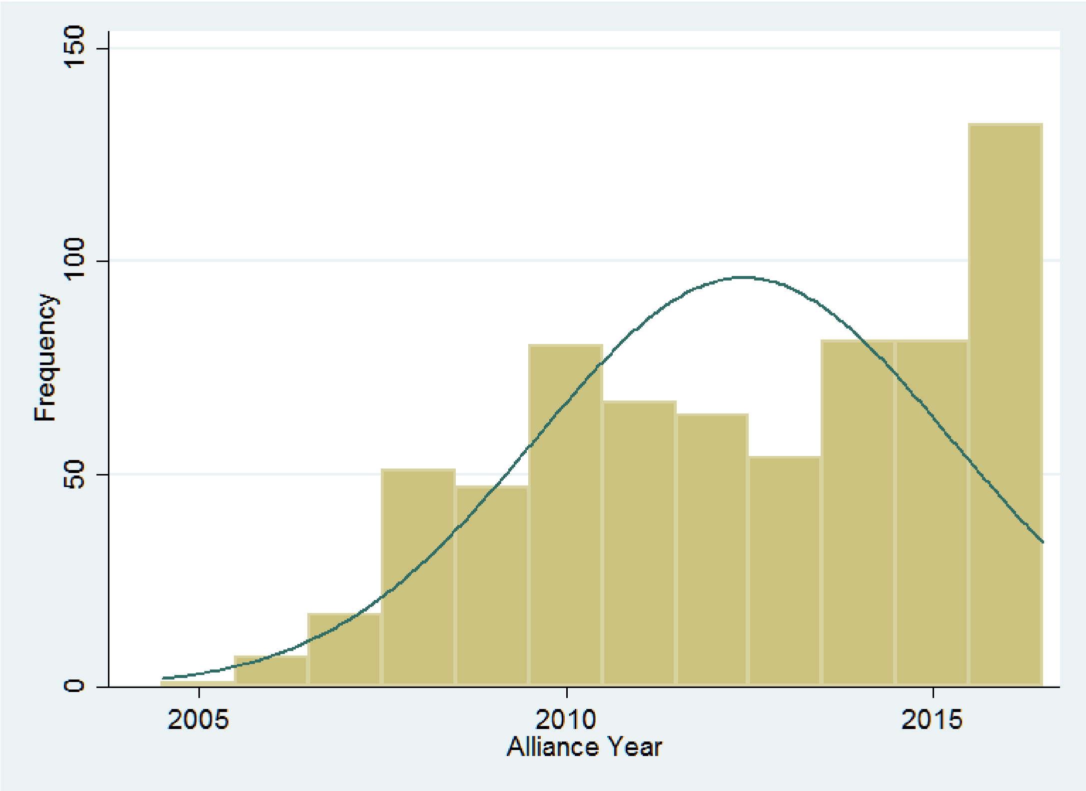

Figure 2. Realized strategic alliances

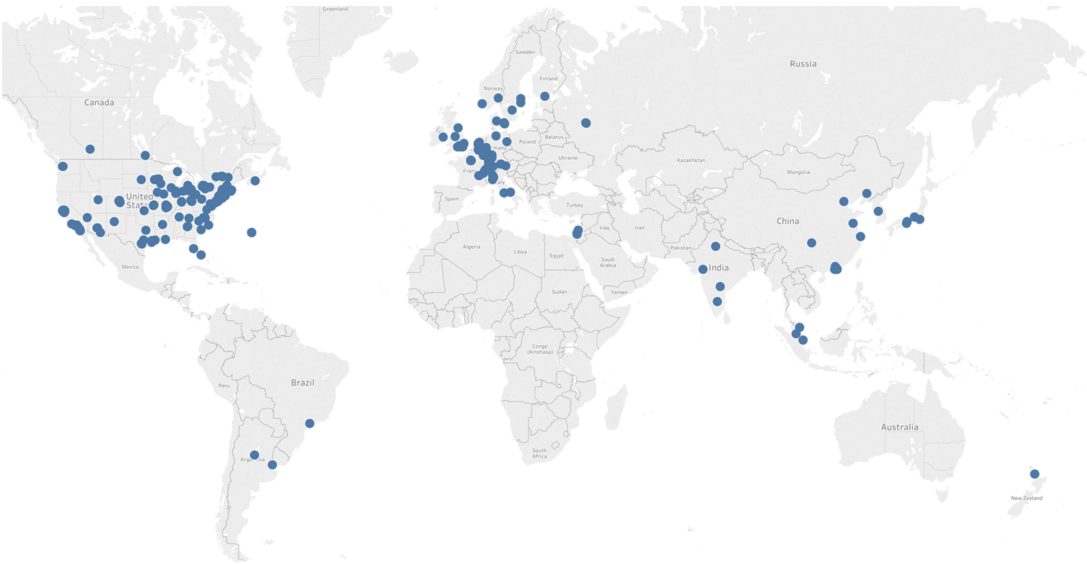

Figure 3. Geographical location of strategic alliance partners

on their VC financing and other company as well as industry characteristics. Table 1, Panel B shows that at the time of their first strategic alliance 24% of the strategic alliance partners in our data set are VC-backed with an average number of 3.34 rounds (median is 2). They usually have more VC investors and a higher fraction of non-US investors than the biotech companies in our sample. Their VC investors have some slightly better experience, but slightly weaker networks. However, the difference is statistically not significant. Strategic alliance partners typically are older than the biotech companies since the median age is 24 years (mean is 46.84). 100 (20.1%) of the alliance partners are in the biotechnology industry, 110 (22.1%) are in the pharmaceutical industry and the remaining 57.8% are in other industries.

3 Realized and counterfactual strategic alliances

3.1 Construction of the counterfactual alliances sample

Besides the sample of 683 realized strategic alliances, we build a sample of counterfactual (potential) alliances. This sample consists of dyad combinations between biotech companies and strategic partners that were possible, but never occured. These two samples should help us in answering the question, which factors determine whether two particular companies form an alliance. For this purpose, we construct a binary dependent variable which equals one for realized alliances and zero for counterfactual alliances.

Figure 4 visualizes the building of the counterfactuals. To make clear how we construct the counterfactual alliances sample, let us take an example of companies C, D and E, with three alliance partners M, N and O. All these three realized alliances C-M, D-N, E-O will be included in the sample of realized alliances (the total number of such alliances in the entire sample is 683) and the dependent variable will be one. To construct the counterfactual matches (dependent variable is zero) for each of these realized alliances, we proceed in the following way. We start with the alliance D-N and consider companies that were active as strategic partners at the same time, but entered an alliance with a different biotech company than D. More specifically, we consider three closest strategic alliances that were closed prior and three closest strategic alliances that were closed after the alliance between D and N. When we apply this procedure to all 683 realized alliances from our sample, we end up with 4,098 counterfactual alliances. We obtain six counterfactual matches for each realized alliance. In our example, the counterfactual alliances for the realized alliance D-N are D-K, D-L, D-M, D-O, D-P and D-Q.

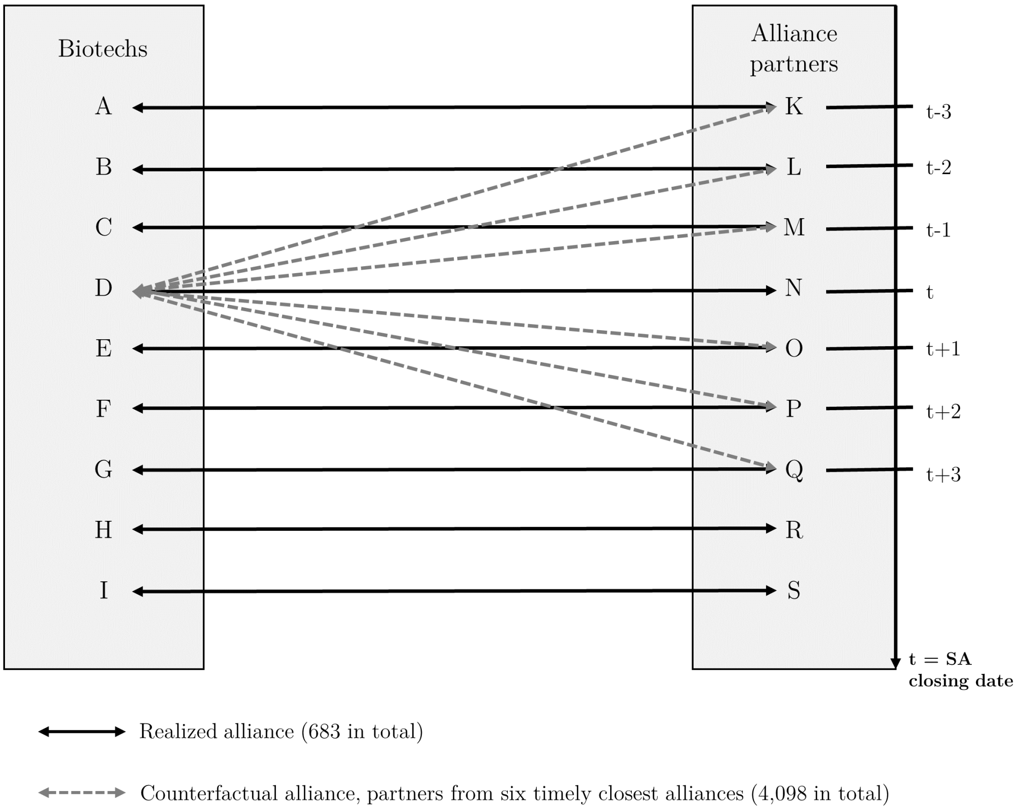

Figure 4. Building of counterfactual alliances sample

3.2 Descriptive statistics for the realized and counterfactual alliances

This section compares the characteristics of the realized and counterfactual alliances. For each (realized and counterfactual) alliance, we have company characteristics of the biotech company and its (potential) alliance partners as well as dyad-specific characteristics.

In Table 2, we focus on whether the two companies that form (or potentially could form) an alliance are both VC-backed, share a common VC (same VC-backed) or were financed by VCs that share a common network (syndication network (dummy)). Out of the 683 realized strategic alliances, we have 388 pairs (56.8%) where only the biotech company was VC-backed and 295 pairs (43.2%) where both partners were VC-backed. In the counterfactuals, we have 2,736 matches (66.8%) where only the biotech is VC-backed and 1,362 matches (33.2%) where both partners were 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 same VC-backed alliances, which is 7.5% for realized alliances and only 3.2% in the counterfactual alliances. According to the topic of this paper, the differences with respect to the syndication network are the most interesting. In 27.5% of realized, and only in 18.2% of counterfactual alliances, the alliance partners share the same VC network and have prior ties. The difference ist statistically significant. The syndication network is also stronger for the realized than for the counterfactual alliances. If we proxy the strength of the network between two VCs by the number of joint investments in the past (if no joint investments happened in the past, then the joint network equals zero), we come up with a total network (of all common syndication networks in one alliance pair) of 17 ties in realized and 6.95 in counterfactual alliances on average, the difference being statistically significant. Also the mean common network (per VC) is significantly larger in realized than in counterfactual alliances (0.20 and 0.08 respectively). These numbers suggest that VC syndication networks are relevant in improving access to potential alliance partners.

We also compare dyad characteristics of realized and counterfactual alliances in Table 2. We focus on differences in geographical distance (in km), technological distance (same industry) and maturity. There is a difference in geographical distance. It amounts to 3,963 km on average in a sample of realized alliances and 4,109 km on average in a sample of counterfactual alliances. The difference in means, however, is statistically not significant. We do not find statistically significant differences in the technological distance. Finally, the mean of the differences in ages between both partners is higher for realized alliances (47.13 years) than for counterfactual alliances (39.93 years). The difference is statistically significant.

4 The role of prior VC ties in alliance formation

We start with differentiating between the different alliance types. In Table 3, we use the sample of all realized alliances to show how the type of the alliance that the biotech company closes is related to the characteristics of the VCs that finance this biotech, in particular to the size of their networks. Panel A shows relative risk ratios (RRR) where the base category is an alliance with a non VC-backed partner. The table shows that it is more likely that an alliance is formed with a company that is either financed by the same VC or by a network VC, if prior ties of the involved VCs are stronger (compared to a partner that is not backed by VC). In addition, a higher share of non US-based investors is related to a higher likelihood of closing an alliance where the investors have prior ties. The distance variable (between the strategic partners) is statistically not significant. Panel B shows average marginal effects. Stronger prior VC ties predict a higher likelihood of alliance formations where both partners are either financed by the same VC or by a prior syndication VC. The effect of prior ties in the syndication network is higher than the same VC effect (11.5 vs. 4.3 percentage points). This result leads us to the most interesting part of the analysis where we investigate how the probability of closing an alliance between a biotech company i and a partner j is related to sharing a common VC and a common syndication network. To analyze this probability, we employ cross-sectional logistic models. Our dependent variable is binary and takes the value 1 if i and j close a strategic alliance and zero otherwise. For this analysis, we use the pairs of realized and counterfactual alliances.

We expect the likelihood of forming a strategic alliance to increase when both companies are backed by the same VC or by two different VCs from the same syndication network. By using a dyad between a biotech company and a (potential) partner as the unit of analysis, we are able to extend the investigation and include dyad-specific characteristics as controls. Furthermore, we add year dummies to account for time-specific effects.

Table 4 presents the partial effects at the averages, i.e. the marginal effects of each variable when the covariates are included at their sample means. First, the positive and significant coefficient on the binary variable *Both VC-backed*, which holds across all regressions, suggests that the likelihood to form an alliance increases when the potential strategic partner is VC-backed. Column (1) shows that an alliance is more likely to be realized when the two partners share a common VC. The probability is higher by 7.8 percentage points. The combined syndication network of all participating VCs *Syndication network (sum)* in column (2) is positive and statistically significant at the 1% level. The economic magnitude is large. A change by one standard deviation corresponds to a positive change in the alliance probability by 3.7 percentage points. Both effects are statistically significant. Interestingly, when we include in column (3) the two variables jointly, the effect of prior ties does not change much in its magnitude and significance, while the *Same VC-backed* variable gets much smaller and looses its statistical significance. These results point out the important role that prior ties among VCs play in alliance formation. Whereas in previous studies the result showed that sharing a common VC is associated with a higher probability of having an alliance, our results point out the fact that the underlying VC network plays the more crucial role in building strategic alliances. Connections in the investment history of the involved VCs support the conclusion that prior VC ties are more beneficial for forming a strategic alliance than simply having a common VC involvement. In columns (4) and (5), we repeat the analysis from columns (2) and (3) with an alternative syndication network variable. Instead of considering the entire network, we include the average number of prior ties of the participating VCs. This variable is also statistically and economically significant. The same VC effect gets statistically and economically smaller, but remains significant.

In the next step, we are interested in how the same VC and the prior VC ties effects vary with changing geographical and technological distances. Table 5 suggests that same VC-backing and large networks are beneficial in mitigating geographical distances. The interaction terms in columns (1) and (3) have positive signs. Thus, the negative effect of distance is lower when both partners share a common VC or if they were financed by different VCs with a large common syndication network. As to the technological distance, Table 4 suggests that the match is more likely if the two partners are from different industries. Probably, companies tend to diversify through this channel. We find that this distance further increases, when companies were financed by VCs with large networks. A potential explanation is that well-networked VCs enable a better diversification into other sectors. Typically diversified alliances would be associated with larger information asymmetries than focused alliances, but VCs with large common syndication networks (column (4)) and also VCs with a large average syndication networks (column (6)) may be able to reduce these asymmetries.

5 Robustness and extensions

5.1 Alternative counterfactual alliances samples: propensity score matching

In this section, we construct two additional counterfactual alliances samples. Our starting point is the total number of realized strategic alliances (683). Then, we create all possible combinations between biotech companies and strategic alliance partners. Next, we apply propensity score matching (PSM) and we match six nearest neighbours to each realized alliance. In this first version, it is possible that the biotech company in the counterfactual alliance pair is not the same company as in the realized alliance pair. We match (hypothetical) alliance pairs to each realized alliance pair. The propensity scores are estimated with logistic regressions and explanatory variables are the foundation year of the biotech company, the number of patents the biotech company was granted, the foundation year of the strategic alliance partner, a dummy variable that equals one if both partners are in the same industry (and zero otherwise), the continent the partner is located (categorical variable), and the number of patents the partner was granted.

The second version of the alternative counterfactual alliances sample is also based on PSM and the same observable variables as in the first version. However, in this version, we match counterfactuals under the condition that the biotech company in the counterfactual alliance pair is equal to the biotech company in the realized alliance pair.

Table 6 shows the results of the multivariate analyses with different alternative counterfactual alliances samples. Since we estimated the probability of an alliance based on observable variables, we do not include them in these analyses anymore. We are interested in the syndication network coefficients. In all estimations the coefficients are positive and statistically significant. Columns (1) to (5) show the results based on the first version of the alternative sample. When we include the measure of prior ties (e.g. in columns (3) and (5)) the effect of *Same VC-backed* becomes smaller. Columns (6) to (10) show the results based on the second version of the alternative sample. The effect of *Same VC-backed* becomes smaller again. In column (8) the effect is not even statistically significant anymore. We include time fixed effects in all regressions.

5.2 IPO exit probability

Finally, we look at the IPO exit. The results in Table 7 suggest that companies with alliances among partners from connected VCs realize IPOs more often than companies which have alliances with VC-backed partners from not-connected VCs. Having at least one alliance with a same VC-backed partner increases the likelihood of an IPO by 14.7 percentage points. Compared to that, having at least one alliance with a VC-backed partner from a connected VC is associated with a 26.9 percentage points increase.

6 Conclusion

This paper advances our knowledge of VC-backed companies' development. We find out that the scope of the VC network grounded in previous syndication efforts among VC investors may facilitate cooperation between portfolio companies from different VCs' portfolios. More specifically, our results suggest that two companies whose VCs share a common network, based on prior joint investments, are more likely to enter an 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 portfolio and they share this knowledge with their closely connected peers. We also suggest that VCs that share a joint network may serve as a certification device, and as such mitigate the information problems between involved alliance partners. In addition, our results support the conclusion that connected VCs help portfolio companies in overcoming geographical and technological distances towards the potential alliance partners. Finally, we show that companies with alliances having partners from connected VCs realize IPOs more often.

Our research has implications for the academic debate on alliance formation and factors that facilitate it. We argue that VCs serve as a certification device and reduce transaction costs, as well as asymmetric information problems associated with alliance formation. We demonstrate that the scope and extent of previous syndication efforts among VCs may facilitate cooperation efforts among portfolio companies from different portfolios.

These results on the value that syndication networks may generate are important for the industry as well. For entrepreneurs who decide which VCs to tap for financing, our results stress the importance of VC networks towards other VCs and suggest that entrepreneurs should take a careful look at the VC network partners and their prior and existing portfolios.

An important feature of our modelling approach is that each realized and each counterfactual alliance have a time dimension so that we also can investigate how time since VC funding affects the likelihood of forming an alliance. On the one hand, companies may cooperate, which are at the same time in a VC portfolio (or in a portfolio from a syndication network partner). On the other hand, companies formerly backed by a VC may close a cooperation with companies from this VC's current or previous portfolio (or a portfolio from a syndication network partner) because the trusted VC may serve as a certification device. We expect the VC effect to be especially strong when the companies are still in the VC's portfolio, because in this case the VC has detailed information about both potential partners. Also, when both companies are still in the VC's portfolio, the VC typically exerts a strong control which will have a disciplining effect on the companies' management not to engage in opportunistic behavior. It is on our future agenda to investigate these effects in detail.

However, as the companies in the VC portfolio are still very young, there might not be enough money to be spent on external growth, and also the need to grow rapidly will not be at focus in the very early stage. Thus, the time effect could also be curvilinear. Consequently, our next question is how the strength of the VC effect evolves over time, in particular, whether this effect persists when companies are exited.

Another topic that deserves a deeper investigation is how VC effects (same VCs, same network VCs) change with larger information asymmetries and agency costs. While we have shown that VC effects are larger for companies that suffer from greater geographical and technological distance, further research could focus on institutional distance or company-specific and industry-specific opacity. Finally, we have only touched the relationship between the alliance type and success. Further research is needed in this area to improve our understanding of these links.

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Tables

Table 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
Investors 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
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
Investors 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
VC ties	235.67	196.58	0.00	911.67	204.38

Legend: This table presents descriptive statistics for the biotech companies and their strategic alliance partners. The statistics, with the exception of the *IPO dummy*, are calculated at the time of the biotech's first strategic alliance (Panel A) or at the time of the strategic alliance partner's first strategic alliance (Panel B). *Age* represents the age of the companies in years. *VC rounds* counts the number of VC investment rounds in the biotech company or strategic alliance partner. *Patents* is the number of patents the biotech applied for. *VC dummy* is a dummy variable that equals one if the strategic alliance partner is VC-backed. *Investors count* is the number of involved VC investors. *Foreign VCs* is the ratio between the number of non-US VC investors to the total number of VC investors. *VC experience* is the number of unique VC investment rounds of the involved VC investors. *VC ties* is the number of the total unique co-investors of the involved VC-investors. *IPO dummy* is a dummy variable that equals one if the biotech company went public.

Table 2. Company and dyad characteristics: realized and counterfactual alliances

	Count	Non-VC	Both VC-backed	Same VC-backed	Syndication network (dummy)	Syndication network (sum)	Syndication network (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	6.95	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* counts the number of alliances where the alliance partner is not backed by VC. *Both VC-backed* counts the number of alliances where both partners are VC-backed. *Same VC-backed* is a dummy variable that equals one if there is at least one common VC in an alliance pair, and zero otherwise. *Syndication network (dummy)* is a dummy variable that equals one if the two partners share at least one common VC syndication network. *Syndication network (sum)* is the sum of all common syndication networks in one alliance pair. *Syndication network (mean)* is the mean of all common syndication networks in one alliance pair. *Distance* is the geographical distance in km between two partners. *Same industry* is a dummy variable that equals one if both partners operate in the same industry, and zero otherwise. *Age difference* is the mean of the difference in ages between both partners. t-value is the result of the mean difference test between (2) and (1). z-value is the result of a rank-sum test. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 3. Multinomial logistic regressions with realized alliances

	Panel A: RRR - Category 1: Non VC-backed partner (Base)			**Panel B:** Average Marginal Effects			
	Cat.2 Both VC-backed	Cat.3 Same VC-backed	Cat.4 Syndication network	Cat.1 Non VC-backed partner	Cat.2 Both VC-backed	Cat.3 Same VC-backed	Cat.4 Syndication network
VC ties	0.8755	2.5883***	2.2965***	-0.1266***	-0.0310***	0.0428***	0.1148***
	(0.0916)	(0.5271)	(0.2737)	(0.0172)	(0.0074)	(0.0128)	(0.0167)
Foreign VCs	1.0249***	1.0405***	1.0314***	-0.0066***	0.0013***	0.0017***	0.0036***
	(0.0061)	(0.0088)	(0.0056)	(0.0008)	(0.0004)	(0.0005)	(0.0008)
Investors count	0.7901***	1.0992***	1.0290	0.0073	-0.0206***	0.0067***	0.0067*
	(0.0418)	(0.0400)	(0.0254)	(0.0050)	(0.0044)	(0.0023)	(0.0037)
Alliances count	0.8931**	0.9955	1.0123	0.0055	-0.0096**	-0.0000	0.0042
	(0.0513)	(0.0474)	(0.0297)	(0.0059)	(0.0047)	(0.0030)	(0.0046)
Distance	0.9456	1.0350	0.9462	0.0088	-0.0038	0.0039	-0.0088
	(0.0594)	(0.0861)	(0.0440)	(0.0085)	(0.0051)	(0.0053)	(0.0073)
Patents	1.5062***	0.9133	0.9648	-0.0170	0.0353***	-0.0071	-0.0111
	(0.1903)	(0.1184)	(0.0839)	(0.0157)	(0.0103)	(0.0081)	(0.0134)
N	683	683	683	683	683	683	683

Legend: Panel A presents relative risk ratios (RRR) for multinomial logistic regressions (base category: *non VC-backed partner*) and Panel B presents average marginal effects. The dependent variable is categorical and equals one if the strategic partner in the alliance is not VC-backed. It equals two if both partners are VC-backed. It equals three if in both partners the same VC is involved. It equals four if in both partners VCs are involved that have a joint syndication history. *VC ties* measures the mean of the log count of unique co-investors of the VCs invested in the biotech. *Foreign VCs* is the percentage share of non US-based VCs involved in the biotech. *Investors count* is the number of involved VCs in the biotech. *Alliances count* is the sequence of the particular alliance of the biotech. *Distance* is the log distance between two strategic partners. *Patents* is the count of patents the biotech applied for (in logs). Robust standard errors are displayed in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 4. Logistic regressions with counterfactuals

DV: Realized alliance	(1)	(2)	(3)	(4)	(5)
Same VC-backed	0.0776***		0.0069		0.0465**
	(0.0219)		(0.0259)		(0.0227)
Syndication network (sum)		0.0042***	0.0042***		
		(0.0006)	(0.0007)		
Syndication network (mean)				0.2802***	0.2533***
				(0.0495)	(0.0505)
Distance	-0.0104***	-0.0109***	-0.0109***	-0.0102***	-0.0101***
	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Same industry	-0.0120	-0.0193	-0.0193	-0.0213*	-0.0216*
	(0.0129)	(0.0127)	(0.0127)	(0.0128)	(0.0128)
Both VC-backed	0.0437***	0.0192	0.0189	0.0256**	0.0219*
	(0.0117)	(0.0119)	(0.0119)	(0.0121)	(0.0122)
Age difference	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Patents	0.0002	-0.0022	-0.0021	-0.0001	-0.0001
	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)
Year Dummies	Yes	Yes	Yes	Yes	Yes
N	4,781	4,781	4,781	4,781	4,781

Legend: This table presents partial effects at the averages from logistic regressions with 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 there was at least one common VC in the biotech company and its strategic alliance partner, and zero otherwise. *Syndication network (sum)* is the total number of common joint investments of the biotech VC and the alliance partner VC (in logs). *Syndication network (mean)* is the mean number of common joint investments of the biotech VC and the alliance partner VC over all networks (in logs). *Distance* is the log of the geographical distance between the partners. *Same industry* is a dummy variable that equals one if both partners operate in the same industry, and zero otherwise. *Both VC-backed* is a dummy variable that equals one if both partners are backed by VC, and zero otherwise. *Age difference* measures the absolute difference in the ages of both alliance partners. *Patents* is the number of patents the biotech applied for (in logs). Robust standard errors are displayed in parentheses. A constant is included in all regressions. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 5. OLS regressions with interaction effects

DV: Realized alliance	(1)	(2)	(3)	(4)	(5)	(6)
Same VC-backed	-0.1462	0.1142***				
	(0.0892)	(0.0355)				
Syndication network (sum)			0.0010	0.0078***		
			(0.0027)	(0.0009)		
Syndication network (mean)					0.0439	0.5410***
					(0.2082)	(0.0885)
Distance	-0.0138***	-0.0116***	-0.0140***	-0.0121***	-0.0134***	-0.0113***
	(0.0030)	(0.0029)	(0.0031)	(0.0029)	(0.0032)	(0.0029)
Same industry	-0.0112	-0.0113	-0.0185	-0.0096	-0.0216	-0.0111
	(0.0133)	(0.0137)	(0.0133)	(0.0140)	(0.0134)	(0.0144)
Same VC-backed	0.0356***					
x Distance	(0.0119)					
Same VC-backed		-0.0129				
x Same industry		(0.0533)				
Syndication network (sum)			0.0007**			
x Distance			(0.0003)			
Syndication network (sum)				-0.0030**		
x Same industry				(0.0013)		
Syndication network (mean)					0.0500*	
x Distance					(0.0273)	
Syndication network (mean)						-0.2347**
x Same industry						(0.1122)
Both VC-backed	0.0417***	0.0422***	0.0135	0.0106	0.0194	0.0161
	(0.0113)	(0.0113)	(0.0118)	(0.0118)	(0.0120)	(0.0122)
Age difference	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Patents	0.0003	0.0002	-0.0019	-0.0022	-0.0001	-0.0002
	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0167	0.0149	0.0288	0.0290	0.0212	0.0215
N	4,781	4,781	4,781	4,781	4,781	4,781

Legend: This table presents results from 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 there was at least one common VC in the biotech company and its strategic alliance partner, and zero otherwise. *Syndication network (sum)* is the total number of common joint investments of the biotech VC and the alliance partner VC (in logs). *Syndication network (mean)* is the mean number of common joint investments of the biotech VC and the alliance partner VC over all networks (in logs). *Distance* is the log of the geographical distance between the partners. *Same industry* is a dummy variable that equals one if both partners operate in the same industry, and zero otherwise. *Both VC-backed* is a dummy variable that equals one if both partners are backed by VC, and zero otherwise. *Age difference* is the absolute difference in the ages of both alliance partners. *Patents* is the number of patents the biotech applied for (in logs). Robust standard errors are displayed in parentheses. A constant is included in all regressions. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 6. Logistic regressions with counterfactuals: alternative samples after propensity score matching (PSM)

	Version 1: PSM of alliance pairs					**Version 2:** PSM of alliance partners				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Same VC-backed	0.1303***		0.0493*		0.1037***	0.0936***		0.0411		0.0742***
	(0.0222)		(0.0286)		(0.0235)	(0.0218)		(0.0279)		(0.0230)
Syndication network (sum)		0.0027***	0.0023***				0.0017***	0.0014***		
		(0.0004)	(0.0005)				(0.0003)	(0.0004)		
Syndication network (mean)				0.1451***	0.1103***				0.1109***	0.0836***
				(0.0298)	(0.0293)				(0.0279)	(0.0293)
Both VC-backed	0.0059	-0.0131	-0.0140	-0.0034	-0.0095	0.0274**	0.0155	0.0145	0.0192	0.0145
	(0.0108)	(0.0113)	(0.0113)	(0.0113)	(0.0113)	(0.0112)	(0.0115)	(0.0115)	(0.0118)	(0.0119)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,781	4,781	4,781	4,781	4,781	4,781	4,781	4,781	4,781	4,781

Legend: This table presents partial effects at the averages from logistic regressions with 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 there was at least one common VC in the biotech company and its strategic alliance partner, and zero otherwise. Syndication network (sum) is the total number of common joint investments of the biotech VC and the alliance partner VC (in logs). Syndication network (mean) is the mean number of common joint investments of the biotech VC and the alliance partner VC over all networks (in logs). Both VC-backed is a dummy variable that equals one if both partners are backed by VC, and zero otherwise. Robust standard errors are displayed in parentheses. A constant is included in all regressions. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 7. The effect on the likelihood of IPOs

DV: IPO dummy	(1)	(2)	(3)	(4)	(5)	(6)
Both VC-backed	0.0839	-0.1076	0.0894	0.0996	0.0874	0.0414
	(0.0704)	(0.1320)	(0.0688)	(0.0668)	(0.0694)	(0.0724)
Same VC-backed (dummy)	0.1471**					
	(0.0728)					
Syndication network (dummy)		0.2693**				
		(0.1247)				
Same VC-backed (sum)			0.0649***			
			(0.0203)			
Syndication network (sum)				0.0004**		
				(0.0002)		
Same VC-backed (mean)					0.1142**	
					(0.0545)	
Syndication network (mean)						0.0017**
						(0.0008)
Patents (sum)	0.0019*	0.0019*	0.0022**	0.0018*	0.0020*	0.0014
	(0.0011)	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0012)
Foreign VCs (dummy)	0.2180**	0.2242**	0.2141**	0.2591**	0.2145**	0.2375**
	(0.1012)	(0.0981)	(0.1023)	(0.1085)	(0.1029)	(0.1023)
Alliances count (sum)	-0.0797	-0.0707	-0.0989	-0.1300*	-0.0457	-0.0456
	(0.0622)	(0.0633)	(0.0621)	(0.0705)	(0.0631)	(0.0602)
N	202	202	202	202	202	202

Legend: This table presents partial effects at the averages from logistic regressions with dependent variable *IPO dummy*, which is a dummy variable that equals one if the company went public, and zero otherwise. *Both VC-backed* is a dummy variable that equals one if there was at least one alliance where 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 its strategic alliance partner (over all alliances), and zero otherwise. *Same VC-backed (sum)* and *Same VC-backed (mean)* represent the sum or the mean of *Same VC-backed (dummy)*. *Syndication network (dummy)* is a dummy variable that equals one if the company had at least one alliance where there were VCs with a joint syndication network, and zero otherwise. *Syndication network (sum)* and *Syndication network (mean)* represent the sum or the mean (in logs) of common joint investments of the biotech VC and the alliance partner VC. *Patents (sum)* is the total number of patents the biotech applied for over all alliances (in logs). *Foreign VCs (dummy)* is a dummy variable that equals one if there was at least one alliance with non-US VCs involved. *Alliances count (sum)* is the total number of alliances of the biotech (in logs). Robust standard errors are displayed in parentheses. A constant is included in all regressions. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.