



Getting tired of your friends: The dynamics of venture capital relationships

Qianqian Du^a, Thomas Hellmann^{b,*}

^a Peter B. Gustavson School of Business, University of Victoria, Victoria, BC, Canada

^b Saïd Business School, University of Oxford, Park End Street, Oxford OX1 1HP, UK

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ABSTRACT

We empirically examine how venture capitalists adjust coinvestor relationships over time. We identify a fundamental trade-off where the benefits of familiarity are weighed against the opportunity costs of coinvesting with other syndication partners. Using US data, we find that venture capitalists dynamically adjust their relationship intensities by gradually disengaging from overly deep relationships. More centrally networked investors are more cautious with disengaging. In hot investment markets investors disengage more readily from existing relationships, but new relationships forged in hot market are less enduring. Perhaps surprisingly, we find a negative relationship between deeper prior relationships and investment performance.

1. Introduction

There are benefits and costs to having a prior relationship. Much of the academic literature emphasises the benefits of having relationships, due to higher trust, more reciprocity, and lower communication costs. However, there can also be some opportunity costs of having prior relationships. One therefore needs to remain open to new opportunities, because limiting oneself to a few deep relationships can lead to loss of breadth and eventually poorer performance.

Much of the prior relationship literature in finance, such as the relationship banking literature (Rajan, 1992; Bolton et al., 2016), is concerned with established investors that operate in relatively stable environments. In this paper we build on the prior research of Sorenson and Stuart (2001), Brander et al. (2002), and Hochberg et al. (2007, 2010, 2015) and consider the evolution of relationships among venture capitalists (VCs henceforth) who operate in fast-paced environments.

Specifically, we consider how VCs manage the intensity of their coinvestment relationships, and how this affects their investment performance. VCs constantly face choices about how to adjust their set of relationships. Our central research question is how VCs dynamically trade off the benefits and costs of deepening relationships. We examine how this trade-off is influenced by investor characteristics and market factors. Finally, we ask how it affects performance.

Our conceptual starting point is the trade-off between the benefits of familiarity and trust versus the opportunity costs of missing out on

alternative opportunities. Having more prior coinvestments builds trust, increases partner familiarity, and reduces transaction costs. However, deeper relationships can also have opportunity costs, especially when VCs overcommit to existing relationships, at the detriment of fostering newer relationships. VCs risk forgoing coinvestments with other partners and thus risk getting less exposure to new ideas, which can be particularly costly in fast-paced environments.

For our empirical analysis we obtain data from the Thomson Reuters Eikon which gives us a long history of VC investments in the US from 1985 to 2020. The prior literature on VC relationships typically uses a cross-sectional approach. This means looking at one dyadic relationship (i.e., one pair of VC investors) and comparing it to other dyadic relationships. The main dependent variable is initially the likelihood of subsequent coinvestments, then investment performance. A cross-sectional approach is appropriate for examining the overall benefits and costs of having relationships. Such an analysis focuses on how *different dyadic pairs* compare with each other. However, in this paper we are interested in how, *within a given dyadic relationship*, partners adjust the intensity over time. This requires a novel empirical approach that focuses on longitudinal variation. We introduce dyadic fixed effects that fully eliminate all cross-sectional (i.e., cross-dyad) variation, and thus focuses only on the longitudinal (i.e., within-dyad) variation. The distinction turns out to be empirically important. In a cross-sectional setting without dyadic fixed effects, we find a positive relationship between prior and subsequent coinvestments. Intuitively this says that

* Corresponding author.

E-mail address: thomas.hellmann@sbs.ox.ac.uk (T. Hellmann).

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“better friends like to continue working more with each other” (i.e., they coinvest more with each other, relative to more distant partners). However, in a longitudinal setting with dyadic fixed effects, this relationship turns negative. Intuitively this says that “when friends get too close, they get tired of each other” (i.e., periods of more coinvestments are followed by periods of fewer coinvestments).

The willingness to deepen coinvestment relationships might vary across investors. VCs with a central network position are eager to maintain a good reputation (Hochberg et al., 2007, 2015). They may therefore be more cautious to distance themselves from existing relationships. Moreover, VCs at the center of the network already have wide access to new information and may therefore be less worried about missing out on new trends. We thus conjecture, and empirically verify, that more central VCs adjust their relationships more slowly, disengaging more cautiously from their established relationships.

Another important factor concerns the market environment within which VC relationships operate. Building on Gompers and Lerner (2001), Sorenson and Stuart (2008), Nanda and Rhodes-Kropf (2013, 2017) and Janeway et al. (2021), we consider the cyclicity of investments. ‘Hot’ VC markets are characterized by intense deal-making, quick decision frames, and high levels of experimentation. Empirically, we find that relationships adjust more in times when the VC market is hot. Interestingly, VCs also disengage more quickly from relationships built in such hot markets.

To empirically analyse the question of performance we consider exits (IPOs and acquisitions) of the underlying portfolio companies. A benefit-centric view of relationships might predict a positive association between deeper investor relationships and venture performance. However, this prediction turns out to be empirically false. In fact, we find that deeper relationships are associated with lower venture performance, even after controlling for endogeneity. This result may be surprising but can be readily explained by the dynamic adjustment process described above. Specifically, the trade-off between the benefit of familiarity vs. the opportunity cost of missed alternatives involves a delicate adjustment process where VCs gradually disengage from deeper relationships without wanting to undermine trust. Consistent with this, we empirically find that negative performance manifests over relative short time horizons (within 2 years), whereas disengagement happens over longer time horizons (up to 5 years).

The remainder of the paper is structured as follows. Section 2 discusses the prior literature and develops the main hypotheses. Section 3 describes the data. Section 4 discusses the main empirical analysis. Section 5 concludes.

2. Literature and hypotheses

It has long been recognized that VCs play a critical role in the development of entrepreneurial companies (Sahlman, 1990; Hellmann and Puri, 2002; Bernstein et al., 2016). A prior literature examines the determinants and consequences of syndicated VC investment; see in particular Lerner (1994), Brander et al. (2002), Casamatta and Haritchabalet (2007). Closely related is a literature that examines the role of VC networks; see in particular Sorenson and Stuart (2001, 2008) and Hochberg et al. (2007, 2010). A more recent literature examines various nuances of these relationships, and the frictions that may arise; see in particular Hochberg et al. (2015), Du (2016), and Nanda and Rhodes-Kropf (2018).

Our starting point is a cost benefit trade-off between nurturing existing relationships versus forging new ones. For the benefit of deepening relationships, we refer to the sociological work of Gulati (1995,

1999) who emphasise the benefits of familiarity and trust.¹ The work of Brander et al. (2002) and Hochberg et al. (2007) provide a more economics-based discussion of these arguments. However, there is also a prior literature that emphasises the potential dark side of relationships. The seminal work of Granovetter (1973) already suggested not to get tied down too deeply in a few deep relationships, and the work of Uzzi (1996) explicitly discusses the dangers of over-embeddedness. From a finance perspective, this can be viewed as the opportunity cost of overly deep relationships. Consistent with that, Ter Wal et al. (2016) empirically show that VCs constantly gather fresh information about emerging opportunities and trends. Thus, VCs constantly need to think how to dynamically readjust their relationships to capture these novel trends.²

We conjecture a dynamic adjustment process where VCs constantly readjust the intensity of their relationships to maintain an overall balance in their portfolios. If two VCs find themselves coinvesting a lot for some period of time, they will want to rebalance the relationship and gradually decrease its intensity, in order to create room for other relationships to grow. Some retrenchment is necessary to avoid relational inertia, and to create room for other relationships to develop. However, such retrenchment is likely to be gradual, not to lose the trust that has already been established. We therefore state our first hypothesis as follows:

Hypothesis (H1). *Looking at a dyadic relationship over time, the dynamic adjustment process generates a negative relationship between the past history of coinvestments and the likelihood of making coinvestments going forward.*

We now use Hypothesis 1 as our starting point to understand how this adjustment process depends on networks and market conditions. Building on Hochberg et al. (2007), we ask whether more prominent players in the network adjust differently. On the benefit side, we note that more central players rely on a good reputation and on-going trust with their coinvestors to maintain their prominence within the network. They are particularly careful not to upset their existing relationships in the pursuit of new opportunities. Moreover, more central players don't have the same fears of missing out, given that their central position allows them to keep a pulse of all important market development (Ter Wal et al., 2016). We thus conjecture that VC firms with more central network positions are especially cautious managing their relationships.

Hypothesis (H2). *The dynamic adjustment process from Hypothesis 1 is less pronounced for more central VC pairs.*

The dynamic adjustments of VC relationships may also depend on the external environment. The VC market has strong cyclicity, where “hot” markets with a large number of transactions alternate with “cold” markets that witness much fewer deals (Gompers and Lerner, 2001). Nanda and Rhodes-Kropf (2013, 2017) argue that VCs' investment behaviour changes significantly across such “hot” versus “cold” market and derive the implications for what companies get funded and when. Taking a network relationship perspective, Sorenson and Stuart (2008) empirically find that new relationships are mainly formed in hot markets.³

¹ Surveying this large prior literature, Zhelyazkov and Gulati (2016) conclude that “the literature's overwhelming consensus is that prior collaborations facilitate the development of trust and social attachments that increase the likelihood that actors will select their past partners for future collaborations.”

² In the related context of scientific exploration, McFadyen and Cannella (2004) find that increased interactions with the same co-authors lead to diminished returns to knowledge creation. Baer (2010) further shows that networks are more likely to boost creativity when they afford access to a wide range of different social circles. A recent work by Xia et al. (2023) explores how homophilic preferences, reciprocity, and societal values affects the syndication between Chinese VCs and US VCs across different financing rounds.

³ In a related vein, Zhelyazkov and Tatarynowicz (2021) examine the circumstances under which lower-status VCs coinvest with higher-status VCs. Their evidence suggests that status-asymmetric ties are more easily formed in hot rather than cold markets.

In our context, we ask whether relationship dynamics differ across hot versus cold markets. We would expect that the opportunity cost of missing out on alternative investments is bigger in hot market, when the ‘fear of missing out’ is greatest. Thus, VCs should be more likely to increase their coinvestments with new partners in hot markets, and they may also pay relatively less attention to their existing relationships. At the same time, these new relationships forged in hot markets may also be more experimental (consistent with Nanda and Rhodes-Kropf 2013, 2017). One may thus conjecture that they are less durable, i.e., that it is easier to walk away from relationships built in hot markets. To use an analogy, we hypothesize that friendships forged in difficult times (think ‘war friends’) are stronger than friendships built in easy times (think ‘party friends’). Furthermore, we hypothesize that friendships are more binding in difficult times than in easy times (think prior friendships are more important in war times than in party times).⁴

The first part of Hypothesis 3 focuses on past coinvestments that were forged in either hot or cold markets.

Hypothesis (H3A). *The dynamic adjustment process from Hypothesis 1 is more pronounced if the history of doing more coinvestments occurred in hot markets.*

The second part of Hypothesis 3 focuses on the importance of current market conditions.

Hypothesis (H3B). *The dynamic adjustment process from Hypothesis 1 is more pronounced if the adjustment happens in a market that is currently hot.*

To discuss performance implications, let us briefly review some of the prior related literature. Hochberg et al. (2007) find a positive relationship between network centrality and venture performance. A recent literature on diversity in investment syndicates typically finds a positive relationship between various measures of diversity and venture performance. Gompers et al. (2016) show that VCs with the same ethnic, educational, or career background are more likely to invest together, but actually make poorer investments.⁵ Chemmanur et al. (2016) find that syndicates of domestic and foreign investors outperform those with only domestic or only foreign investors.⁶ Finally, Du (2016) finds that VC firms that coinvest with more heterogeneous partners are more likely to survive in the long run. Relevant to this paper, this suggests that more exploratory investment strategies yield benefits, but only in the longer term.

This prior literature is largely based on a cross-sectional comparison of relationship pairs. Our interest here is to understand the longitudinal aspects of how performance varies over time within a given pair of investors. Specifically, we ask whether, for a given VC dyad, a deeper past relationship leads to higher or lower performance. Building on the trade-off underlying Hypothesis 1, we submit that relationships that are overly close generate lower performance. This is because VCs may place greater weight on the immediate benefits of familiarity and less weight on learning benefits that are less tangible and further out into the future. Whilst their investment opportunities change at an unforgiving pace, VCs may also feel somewhat constrained by social norms of reciprocity.

Hypothesis (H4A). *Looking at a dyadic relationship over time, a history of more past coinvestments leads to poorer coinvestment performance going forward.*

⁴ In a related vein, Babina et al. (2023) provide direct evidence about the importance of “friends during hard times” by looking at inter-firm relationships during the financial crisis of 1929.

⁵ In a related line of research, Hegde and Tumlinson (2014) and Bengtsson and Hsu (2015), look at co-ethnicity between VC investors and entrepreneurs. Ishii and Xuan (2014) perform a similar analysis for social ties between M&A acquirers and targets.

⁶ Bottazzi et al. (2016) find that higher generalized trust between VC firms is associated with lower investment performance. There is also a related literature on cross-border investor networks and their investment behaviours. See Devigne et al. (2016) and Jääskeläinen and Maula (2014).

This first part of Hypothesis 4 looks at the overall link between relationship histories and performance. The second part takes a closer look at the relative speeds with which relationships and performance evolve over time. We already noted that making good investment decisions in a fast-paced environment requires being alert and quickly seizing new opportunities, including with new partners. However, relationships are based on trust and take time to adjust. This tension can affect the relative speeds at which performance and coinvestments adapt over time.

For the second part of Hypothesis 4, we submit that the downsides of overly deep relationships manifest relatively quickly. However, the process of distancing oneself from them may be slower, because of the delicacy of maintaining trust and reciprocity. VCs may even prefer to wait for some evidence of declining performance before starting to disengage from overly deep relationships.

Hypothesis (H4B). *Looking at a dyadic relationship over time, a history of more past coinvestments leads relatively quickly to a decline in performance, and more slowly to a reduction in coinvestments.*

3. Data

3.1. Sample

We obtain the data of US VC investments from the Thomson Reuters Eikon database, formerly known as VentureXpert database or Venture Economics, which provides the most comprehensive coverage of the US VC investment activities. While our original sample of VC investments starts in 1985, we need the first five years of the investment data to construct the coinvestment history variables. The main sample used for the empirical analysis therefore starts in 1990. Although our sample of VC investments ends in 2012, the information regarding the portfolio companies’ IPOs and acquisitions is extended to the end of 2020, giving portfolio companies at least eight more years before evaluating their exit performance.⁷

We focus on the relationships among top 100 VCs. This selection criterion has conceptual and practical benefits. Conceptually it allows us to look at meaningful relationships where the two parties interact frequently and can expect the other party to remain active in the future. Practically we need to build a dataset of potential VC-pairs for each company round. The size of this dataset expands dramatically in the number of VCs. Focusing on the top 100 firms keeps our sample size manageable at approximately 4.4 million observations. To identify the top 100 VCs, we require that a top VC firm started making VC investments before 2002, ensuring that it has invested for at least 10 years in our sample. We identify the top 100 based on their number of rounds invested per year and list these 100 VCs in Table A.1 of the Online Appendix. Our company sample consists of those companies that received one or more investments from at least one of the top 100 VCs. This leads to a sample of 11,084 companies and 38,473 rounds financed by a total of 4,445 VCs. Compared with the full sample of VC investments made in the same period, our sample represents approximately 40 % of all VC-backed companies (28,224 companies in the full sample), 53 % of all financing rounds (72,001 rounds in the full sample), and 68 % of all VCs (6,491 VCs in the full sample).

To study the dynamics of the relationships of VCs, we consider the set of their potential coinvestments. For this we start with all the rounds of the companies in our sample. For each round we then consider all potential VC-pairs. To define the potential set for each round of a portfolio company, we call “involved VCs” those top 100 VCs who invest in the current round, or who invested in any of the previous company rounds.

⁷ To address the “round-splitting” problem discussed by Gompers and Lerner (1999) that one financing round may be mistakenly recorded for multiple rounds, we combine two financing rounds of the same portfolio company as one round if they are financed by the same VCs within three months.

We call them “involved” since they either actually invest in the round, or clearly have the option to do so. We define the rest of the top 100 VCs as “not involved VCs”. For each round there are in principle 9,900 (=100×99) VC pairs to consider. However, this includes mirror images, in the sense that both the pair (VC1, VC2) and (VC2, VC1) are counted. Thus, the number of distinct VC-pairs is 4,950. For any given company-round, there can be three possibilities: either both VCs are involved, only one of the two VCs is involved, or neither is involved. We drop the last category from the sample with the argument that the absence of both investors in a deal does not reveal much about their relationship, it simply says that neither consider the deal involved. This leaves us with a final sample of 4,392,427 VC-pairs involved in a company-round. The VC-pair-in-company-round is thus the unit of observation for our main empirical sample. An example of constructing VC pairs is included in Example B.1 of the Online Appendix.

3.2. Variables

All variables are defined in Table 1. We report our sample statistics in Table 2. The correlation matrix of key variables is reported in Table A.2 of the Online Appendix. Our first dependent variable is a dummy called “Coinvestment” which takes the value 1 if for a given observation both VCs invest in the company round, and 0 otherwise. This measures whether two VC firms, who might be expected to coinvest in a deal, actually do. Among the total of 4,392,427 observations, 0.48 % of them are realized coinvestments made by VC-pairs in the financing rounds.

Our key independent variable, “Joint-history”, measures the relationship history of two VCs based on the number of coinvested rounds they made in the past five years in companies other than the current company. On average, there are 0.84 coinvested rounds made by any pair of VCs in the past five years. Importantly, the “Joint-history” variable deliberately excludes any prior coinvestments in the same company, in order to avoid any mechanical relationships. Moreover, if two VCs have already invested in a focal company, and now face a new round, we should be less surprised to find another coinvestment. We control for this using the variable “Follow-on” which equals one if both VCs already coinvested in an earlier round of the same company before the current round. Conditional on having made a coinvestment in an earlier round, 64 % lead to a follow-on coinvestment. We consistently find that the “Follow-on” variable is a powerful control. The two relationship variables, “Follow-on” and “Joint-history”, reveal the pattern of investment relationships of a pair of VCs in the current company and those companies invested earlier, respectively.

We then provide several breakdowns of this coinvestment history by distinguishing different types of past coinvestments. Specifically, we distinguish past relationships made in more recent vs. more distant years, as well as past relationships made in hot vs. cold market. We construct our measure of hot vs. cold markets by interacting every industry with every quarter and calculate the dollar amount invested in each such industry-time-specific cell. We define an industry-quarter cell as a hot market if its total amount of VC investment falls into the top tercile of all the markets in the full sample and a cold market if the total investment amount falls into the bottom tercile. Note that while only 33 % of industry-year cells are classified as hot markets, they contain approximately 68 % of all the dollar amount invested in our sample period.⁸

In Table 2, there are more coinvestments made in earlier years: VCs on average coinvest in 0.47 rounds in earlier years, compared with 0.36 rounds in more recent years. Regarding VCs’ past coinvestments in hot and cold markets: there are an average 0.54 coinvested financing rounds made in hot markets and 0.09 coinvested financing rounds made in cold

⁸ Our baseline model retains the middle tercile, but in Table A.3 in the Online Appendix we report the results dropping the middle tercile; the results remain very similar.

Table 1
Variable definitions.

Variable	Definition
VC pair (VCi and VCj) -in-company-round level:	
Coinvestment	A dummy variable, indicating whether the current financing round is syndicated by VCI and VCj. It is multiplied by 100 in the regressions.
Experience-avg	It is the log of 1 plus the average experience of VCI and VCj. Experience is the number of rounds a VC has invested in the past five years.
Follow-on	A dummy variable, indicating whether VCI and VCj have coinvested in an earlier round of the same company as the company in question.
Industry-avg	It is the average industry match value of VCI and VCj. Industry match value is defined as the percentage of rounds a VC has invested in the current company’s industry in the past five years.
Joint-history	The number of rounds that VCI and VCj have coinvested in all other companies (excluding the current company) in the past five years.
Network centrality	The average normalized degree centrality of a pair of VCs. We first calculate the number of unique coinvestment partners a VC has had in the past five years. We then normalize it to make this measure comparable over time. The network measure is calculated using the UCINET software.
Older-history	For each VC-pair-in-company-round observation in year $t = 0$, it is the number of coinvested rounds by VCI and VCj in years $t = -3$ through $t = -5$.
Past-hot/cold-coinvestments	The number of rounds that VCI and VCj have coinvested in all other companies (excluding the current company) in hot/cold markets in the past five years. We first define a market as the interaction between every quarter and every industry of a portfolio company. We then define a market as hot if its total amount of VC investment falls into the top tercile of all the markets in the full sample, and as cold if it falls into the bottom tercile.
Recent-history	For each VC-pair-in-company-round observation in year $t = 0$, it is the number of coinvested rounds by VCI and VCj in years $t = -1$ and $t = -2$.
Stage-avg	It is the average stage match value of VCI and VCj. Stage match value is defined as the percentage of rounds a VC has invested in the current company’s stage in the past five years.
State-avg	It is the average geographic match value between VCI and VCj. Geographic match value is defined as the percentage of rounds a VC has invested in the current company’s state in the past five years.
Company round level:	
Now-hot /cold	A dummy variable, which is equal to 1 if the current investment is made in a hot/cold market. We first define a market as the interaction between every quarter and every industry of a portfolio company. We then define a market as hot if its total amount of VC investment falls into the top tercile of all the markets in the full sample, and as cold if it falls into the bottom tercile.
Round-amount	It captures the amount of investment provided to a financing round. We use the log of this variable in regressions.
Company level:	
Company-age	It reports the number of years between the founding year of a company and the year of the current financing round.
Exit	A dummy variable, which is equal to 1 if the company has an IPO or gets acquired by another company with a value higher than the total amount of VC investment, and equal to 0 otherwise.
IPO	A dummy variable, which is equal to 1 if the company has an IPO, and equal to 0 otherwise.
Year level:	
Market trend	We construct three market trend proxies, which are measured at the year level. “Deals” capture the total number of financing rounds made by all VCs in a year. “New Deals” captures the total number of new investments, i.e. first round investments made in a year. “VCs” measure the total number of VCs making investments in a year.
Market share	The proportion of financing rounds invested by any of the top VCs relative to all deals in a year.

(continued on next page)

Table 1 (continued)

Variable	Definition
Fixed effects:	
Deal-FE	It includes five sets of dummy variables: the dummies of the year of the current financing round, the dummies of portfolio companies' 6-category industry classification from Thomson Reuters Eikon, the dummies of portfolio companies' states, the dummies of the stages of the company at the current financing round, and the dummies of the round number.
VC FE	It is the dummies of individual VCs.
VC-Pair FE	It is the dummies of VC pairs.

Table 2

Descriptive statistics.

Variable Name	Obs.	Mean	S.D.	5 %	Median	95 %
Coinvestment %	4,392,427	0.48	6.94	0	0	0
Joint-history	4,392,427	0.84	1.83	0	0	4
Follow-on	4,392,427	0	0.05	0	0	0
Experience-avg	4,392,427	128.94	59.82	42.5	122	241
Industry-avg	4,392,427	0.31	0.19	0.05	0.29	0.64
State-avg	4,392,427	0.34	0.27	0.01	0.35	0.77
Stage-avg	4,392,427	0.32	0.13	0.11	0.32	0.51
Round-amount (\$ Million)	4,392,427	14.26	25.16	0.63	8.5	45
Company-age	4,392,427	4.45	4.49	0	4	11
Network centrality	4,392,427	9.10	4.55	3.20	8.39	17.7
Past-hot-coinvestments	4,392,427	0.54	1.34	0	0	3
Past-cold-coinvestments	4,392,427	0.09	0.62	0	0	0
Now-hot	4,392,427	0.73	0.44	0	1	1
Recent-history	4,392,427	0.36	0.92	0	0	2
Older-history	4,392,427	0.47	1.19	0	0	3
Exit	21,260	0.62	0.49	0	1	1
IPO	21,260	0.3	0.46	0	0	1
Industry	Obs.	%	Stage	Obs.	%	
Biotechnology	410,984	9.36	Seed	309,934	7.06	
Communications and Media	824,744	18.78	Early	953,409	21.71	
Computer Related	1,964,628	44.73	Expansion	1,789,853	40.75	
Medical/Health/Life Science	513,698	11.7	Later	1,339,231	30.49	
Non-High-Technology	279,566	6.36	Total	4,392,427	100	
Semiconductors/Others	398,807	9.08				
Total	4,392,427	100				
Top States	Obs.	%	Rounds	Obs.	%	
California	2251,841	51.27	1	718,453	16.36	
Massachusetts	635,441	14.47	2	798,490	18.18	
Texas	211,370	4.81	3	759,001	17.28	
Total	4,392,427	100	Total	4,392,427	100	

markets. Among all observations in our sample, 73 % of current coinvestments are made in hot markets.

The variables discussed so far vary at the level of the VC-pair-in-company-round. Several of our independent variables vary at the level of the individual VC firm-year. In this case we need to aggregate the information across the two VC firms in the pair. To preserve symmetry, we always use the average of the two VC firms. The average number of financing rounds invested by a VC in the past five years is 129. To capture a VC's expertise in the same industry, state, and stage as the company in question, we define "match" values as the percentage of rounds a VC has invested in the target's industry, state, and stage in the past five years. A greater match value indicates more expertise of VCs in the company they are investing in.⁹

⁹ The average industry match of the two VCs is 0.31, suggesting 31% of the VCs' past investments are in the same industry as the company in question. The average state match is 0.34, suggesting 34% of the VCs' past investments are in the same state as the company in question. The average stage match is 0.32, suggesting 32% of the VCs' past investments are in the same stage as the company in question.

Several of our variables relate to the company or company-round. Most important is the eventual company performance. Following the prior VC literature (Phalippou and Gottschalk, 2009; Da Rin et al., 2013), we measure performance in terms of either IPOs or Exits. Exits include IPOs and successful acquisitions, where an acquisition is considered successful as long as its acquisition value is higher than the total amount of investments across all rounds. We find that 30 % of the realized VC-pair-in-company-round observations result in IPOs, and 62 % of them in Exits. These variables will be used as dependent variables.

To measure network centrality of VC firms we use the standard measure of degree centrality (Hochberg et al., 2007). We calculate the

number of unique coinvestment partners a VC has in the past five years. To make this measure comparable over time, we further normalize it by the maximum number of coinvestment partners a VC could possibly have in the past five years. For each observation, we calculate the average "Network Centrality" for each pair of VCs.

The companies financed by the top 100 VCs raise on average \$14.26 million per round. The average time difference between a company's founding date and the date of the first VC round is 4.45 years. The industry distribution of our sample is as follows: 45 % of the observations are from the Computer Related Industry, followed by Communications and Media Industry (19 %), and Medical/Health/Life Science Industries (12 %). In terms of stages, 7 % are seed stage rounds, 22 % early stage, 41 % expansion stage, and 30 % late stage.

4. Empirical analysis

4.1. The evolution of coinvestment relationships

In this section we empirically examine the first hypothesis about a negative relationship between past coinvestments and the likelihood of making further coinvestments going forward. Prior empirical studies are

often based on a *cross-sectional comparison* where the likelihood of forging another joint deal (alliance, coinvestment, etc.) for the “focal pair” is compared to the corresponding likelihood for an *alternative pair*. The standard conjecture is that closer friends are more likely to continue working with each other, because of fit and trust. However, our interest here is the evolution of a focal pair’s relationship, which requires a *longitudinal comparison*. We are interested in the likelihood of a joint deal by the focal pair at a particular point in time, as compared to the likelihood for that *same focal pair* but at a different point in time. Empirically, this requires the distinct econometric methodology of introducing investor-pair fixed effects. Throughout the paper we run linear probability models due to the large number of observations and a large set of fixed effects used in all of our regressions (Wooldridge, 2007). In all regressions the standard errors are double-clustered at the VC-pair level and the company level and reported in the parentheses of regression tables.

The purpose of Table 3 is to explain the construction of our base model and demonstrate the importance of using our novel VC-pair fixed effects. The dependent variable is “Coinvestment”, which is a dummy variable to indicate whether the pair of VCs coinvest in the current round. The table examines what impact the history of past coinvestments has on the likelihood of coinvestment in the current round. In column (1) we only include the “Joint-history” and “Follow-on” as two independent variables. “Joint-history” has a positive and significant impact on the “Coinvestment”. This is consistent with the prior literature that coinvestment is more likely to be made by firms which have coinvested with each other before. “Follow-on” has a large positive and highly significant impact on “Coinvestment”. This says that VCs continue to invest in the company if they already financed its earlier rounds.

In column (2) we add a large number of control variables. A larger financing round also has a positive impact on the likelihood of VCs coinvesting. Company age has a negative effect. Next, we find that several of the match variables are statistically significant. For example, the higher the average industry match of the pair of VCs, the more likely they coinvest. We find similar predictions for state match and stage match. In addition, we included deal fixed effects, which capture the impacts of the calendar year, the industry, the state, the stage of the company, and the round number. In column (3) we further include the individual VC fixed effects for both VCs in a pair. Adding these variables

Table 3

Baseline models. All variables are defined in Table 1. All regressions apply the Linear Probability Model. Standard errors reported in parentheses are double-clustered at the VC-pair level and the company level. We use ***, **, and * to denote significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent Variable:	(1)	(2)	(3)	(4)
	Coinvestment			
Joint-history	0.148*** (0.006)	0.132*** (0.006)	0.125*** (0.007)	-0.065*** (0.008)
Follow-on	56.217*** (0.969)	56.122*** (0.967)	56.096*** (0.966)	55.747*** (0.961)
Experience-avg		0.080*** (0.012)	0.085*** (0.014)	0.253*** (0.017)
Industry-avg		0.951*** (0.047)	1.059*** (0.052)	0.898*** (0.048)
State-avg		0.877*** (0.040)	1.022*** (0.046)	0.939*** (0.046)
Stage-avg		0.307*** (0.042)	0.325*** (0.043)	0.314*** (0.043)
Round-amount		0.153*** (0.005)	0.151*** (0.005)	0.153*** (0.005)
Company-age		-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)
Deal FE	No	Yes	Yes	Yes
VC FE	No	No	Yes	No
VC-Pair FE	No	No	No	Yes
Observations	4,392,427	4,392,427	4,392,427	4,392,427
R-squared	0.190	0.192	0.192	0.195

in column (2) and (3) does not change the prediction that the more often VCs coinvested in the past, the more likely they coinvest in the current round.

In column (4) of Table 3, we replace the individual VC fixed effects in column (3) with VC-pair fixed effects. That is, we examine the dynamics of coinvestment for a given pair of VCs. Compared with column (3), we obtain a very different prediction of “Joint-history”. For a given pair of VCs, the more often they coinvested in the past, the less likely they coinvest in the current round. The economic magnitude of the coefficient is meaningful. An increase of a standard deviation of the “Joint-history” in the past five years (1.83 coinvestments) can decrease the likelihood of them syndicating in the future by 0.12 %, equivalent to 25 % of the average likelihood of coinvestment for the whole sample (0.48 %).

The striking difference between column (3) and (4) is directly related to our discussion of Hypothesis 1. It shows that relationship dynamics are entirely different if examined among all VCs in a pooled regression or for a given pair of VCs in regressions with VC-pair fixed effects. Without the VC-pair fixed effects, the estimation of “Joint-history” captures a cross-sectional comparison of different VC pairs. The positive coefficient in column (3) suggests that relative to VC pairs with weaker past relationships, pairs with deeper past relationships coinvest more often. This suggests that there is some long-term matching among VCs, providing evidence of the importance of relationships. However, the negative coefficient in column (4) suggests that once we look inside specific relationships, there is actually a negative dynamic. This suggests that within a given VC pair, partners distance themselves somewhat if they had done a lot of coinvestments in the past, but also come back to do more deals after a period of being further apart. That is, closer pairs always do more deals together than more distant pairs. But when they get too close, they back off a little – this is what we dub the “getting tired of your friends” effect.

A central part of our argument is that VCs want to disengage from overly deep relationships, in order to free up capacity for learning from other relationships. We thus verify that disengaging from one set of relationships does not just mean doing fewer deals, but actually leads to deepening *other* relationships. We propose that the substitution of network partners underlines the motive of experienced VCs’ departure from their old partners. We provide detailed discussion and empirical evidence in Section 4.6.

4.2. The role of network position

We now examine our second hypothesis that the adjustment process (described under Hypothesis 1 and empirically confirmed in Table 3) is less pronounced for more central partners. We present regression results in Table 4 which adds the network centrality measure to the model of column (4) in Table 3. Column (1) adds just the network centrality measure itself and finds a positive and significant coefficient. This says that VCs with more central network positions make more coinvestments. Column (2) further adds a normalized interaction effect between our main independent variable, “Joint-history”, and our measure of network centrality. The interaction term is positive and significant. Moreover, the main independent variable “Joint-history” continues to have a negative and statistically significant effect. This result shows that more central VCs maintain relationships that last somewhat longer. They disengage relatively less from their closer relationships, i.e., they “get relatively less tired of their friends”.

4.3. The role of hot markets

The two closely related hypotheses 3A and 3B concern the market setting, distinguishing between relationships made in “hot” vs. “cold” markets.

Hypothesis 3 is divided into two parts, the first concerning whether past relationships were made in hot vs. cold markets, the second

Table 4

Network centrality. All variables are defined in Table 1. All regressions apply the Linear Probability Model. Standard errors reported in parentheses are double-clustered at the VC-pair level and the company level. In column (2), we normalize both “Network centrality” and “Joint-history” to run regressions with interaction effects. We use ***, **, and * to denote significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent Variable:	(1) Coinvestment	(2)
Network centrality	0.036*** (0.005)	
Joint-history	-0.072*** (0.008)	
Network centrality x Joint-history		11.804*** (1.506)
Network centrality		0.665*** (0.180)
Joint-history		-6.634*** (0.689)
Deal FE/ VC-pair FE/Controls	Yes	Yes
Observations	4,392,427	4,392,427
R-squared	0.195	0.195

concerning whether markets are currently hot vs. cold. Table 5 reports all the results. Column (1) examines Hypothesis 3A and shows that the negative impact of coinvestments is mainly due to the coinvestments made in past hot markets. Coinvestments made in past cold markets have a positive impact on future coinvestment opportunities.¹⁰ This confirms the notion that friendships forged in difficult times (“war

Table 5

Hot vs. cold markets. All variables are defined in Table 1. All regressions apply the Linear Probability Model. Standard errors reported in parentheses are double-clustered at the VC-pair level and the company level. We use ***, **, and * to denote significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent Variable:	(1)	(2)	(3)
Past-hot-coinvestments	-0.108*** (0.011)		
Past-cold-coinvestments	0.067*** (0.019)		
Joint-history x Now-hot		-0.063*** (0.008)	
Joint-history x Now-cold		0.106*** (0.022)	
Past-hot x Now-hot			-0.081*** (0.011)
Past-hot x Now-cold			-0.321 (0.331)
Past-cold x Now-hot			-0.012 (0.040)
Past-cold x Now-cold			0.133*** (0.026)
Now-hot	-0.020 (0.016)	0.027 (0.016)	0.019 (0.016)
Deal FE/ VC-pair FE/Controls	Yes	Yes	Yes
Observations	4,392,427	4,392,427	4,392,427
R-squared	0.195	0.195	0.195

¹⁰ The economic impacts are also meaningful: an increase of a standard deviation of the “Past-hot-coinvestments” in the past five years (1.34 coinvestments) can decrease the likelihood of them coinvesting in the future by 0.14%, almost a third of the average likelihood of coinvestment for the whole sample, suggesting that relationships built in good times when the market has plenty of investment opportunities are less likely to sustain in the long run. An increase of a standard deviation of the “Past-cold-coinvestments” in the past five years (0.62 coinvestments) can increase the likelihood of them coinvesting in the future by 0.04%, approximately 9% of the average likelihood of coinvestment for the whole sample.

friends”) last longer than friendships forged in easy times (“party friends”).

Column (2) examines Hypothesis 3B and finds that past coinvestments have a negative and significant effect if current markets are hot and a positive impact if current markets are cold, consistent with Column (1). The *t*-test for the significance of the difference between the two coefficients in columns (1) and (2) are significant at 1 % (with a F-statistic of 71.45 in (1) and 56.61 in (2)). This is consistent with Hypothesis 3B that relationships become looser when current market conditions are hot.

In column (3) we report an additional decomposition that distinguishes four types of relationships, based on whether past relationships were hot or cold as well as whether markets are currently hot or cold. We find that the most negative coefficient relates to past hot markets when the current market is also hot. By contrast, relationships made during past cold markets in a currently cold market actually have a positive and significant coefficient. These results fortify the results from columns (1) and (2) and further reinforce the messages from Hypothesis 3A and 3B

4.4. Performance implications

We now examine our fourth hypothesis about the relationship between prior relationships and investment performance. Specifically, Hypothesis 4A argues that a history of doing more coinvestments in the past leads to poorer coinvestment performance going forward. To measure performance, we follow the prior VC literature and use IPOs and Exits to proxy for the performance of VC investments in a company. We first consider simple linear regression models that estimate multivariate correlations and discuss endogeneity shortly thereafter. The empirical results are presented in Table 6. Because the performance is only observed for realized coinvestments, all regressions are based on the subsample of realized coinvested deals. We find that for a given pair of VCs, their past coinvestments are negatively associated with having an IPO, as shown in column (1). The negative impact of “Joint-history” is also economically meaningful: an increase of a standard deviation of the “Joint-history” in the past five years (3.73 coinvestments in the sample of realized syndicates) can decrease the likelihood of IPO in the future by 2 %. In column (2) we use Exit as an alternative measure of investment performance. The results are very similar. An increase of a standard

Table 6

Exit performance. This sample includes realized syndicates only. All variables are defined in Table 1. All regressions apply the Linear Probability Model. Standard errors reported in parentheses are double-clustered at the VC-pair level and the company level. We use ***, **, and * to denote significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent Variable:	(1) IPO	(2) Exit
Joint-history	-0.550*** (0.211)	-0.817*** (0.261)
Follow-on	-1.594* (0.848)	-1.520* (0.882)
Experience-avg	-0.785 (2.536)	-1.365 (2.691)
Industry-avg	-2.777 (7.457)	6.800 (8.030)
State-avg	5.770 (6.606)	22.778*** (7.205)
Stage-avg	-24.111*** (6.550)	-12.194* (7.024)
Round-amount	6.566*** (0.665)	3.597*** (0.716)
Company-age	0.259 (0.268)	0.375 (0.312)
Deal FE	Yes	Yes
VC-Pair FE	Yes	Yes
Observations	19,822	19,822
R-squared	0.438	0.389

deviation of the “Joint-history” in the past five years can decrease the likelihood of Exit in the future by 3 %.

Table 6 establishes correlation but not causation. Since the estimated coefficients may also include selection effects, we use a Heckman two-step approach (Heckman 1979).¹¹ In the first step, we examine how VCs select partners to coinvest in a particular company round. In the second step we examine how a pair of VCs’ joint history affects the success of their coinvested company. We describe how we construct the variables to identify the Heckman model in Example B.2 of the Online Appendix. The regression results are reported in Panel A of Table A.4 in the Online Appendix. To further address the selection between VCs and companies, we construct geography-based instruments following Akerberg and Botticini (2002) and Bottazzi et al. (2008). We report the regression results in Panel B of Table A.4. To summarize, we use two distinct sets of exclusive variables for the first stage. The first set addresses the selection of co-investors and is based on their indirect partners. The second set addresses the selection of companies and is based on the Akerberg and Botticini (2002) approach. The results from Table A.4 show that the main findings from Table 6 remain unaffected, suggesting that unobservable selection is not a major concern for these performance regressions.¹²

Hypothesis 4B is concerned with the relative timing and argues that a history of doing more coinvestments in the past relatively quickly leads to a decline in performance, but more slowly to a reduction in coinvestments. To empirically examine this, we decompose prior relationships into more recent vs. older coinvestments. Suppose a pair of VCs are considering coinvesting at time $t = 0$, then we classify their coinvestments made in years $t = -1$ and $t = -2$ as more recent, and those formed in $t = -3$, $t = -4$, and $t = -5$, as older.

Table 7 reports the empirical results. Column (1) shows that while a pair of VCs’ recent history does not have a statistically significant

Table 7

Recent vs. older relationships. In this table, we decompose the past coinvestments into more recent coinvestment history and older coinvestment history. All variables are defined in Table 1. All regressions apply the Linear Probability Model. Standard errors reported in parentheses are double-clustered at the VC-pair level and the company level. We use ***, **, and * to denote significance at the 1 %, 5 %, and 10 % levels, respectively.

Dependent Variable:	(1) Coinvestment	(2) IPO	(3) Exit
Recent-history	0.018 (0.014)	-0.882*** (0.260)	-1.492*** (0.288)
Older-history	-0.122*** (0.008)	-0.336 (0.232)	-0.382 (0.255)
Deal FE/ VC-pair FE/Controls	Yes	Yes	Yes
Observations	4,392,427	19,822	19,822
R-squared	0.195	0.438	0.390

¹¹ This Heckman two-step procedure has been widely used before, including in the work of Bris et al. (2005) and Villalonga and Amit (2006).

¹² Table 6 finds a negative relationship between venture performance and past coinvestments, consistent with Hypothesis 4A. A closely related question concerns the relationship between venture performance and the performance of past coinvestments. We consider this in Table A.5 in the Online Appendix, which also contains the details of our empirical implementation. Again, we find a negative relationship, which suggests that better performance of past coinvestments is a signal that the relationship is maturing. Conversely, lower past performance is followed by better performance, which is consistent with Du (2016) who argues that lower performing deals which may be viewed as learning investment generate better performance down the line.

impact, older history has a negative and significant impact on future coinvestments.¹³ This shows that the negative impact of the past coinvestments on future coinvestments is mainly driven by relatively older relationships. Put differently, it takes some time before VCs are getting tired of their friends. Columns (2) and (3) examine how more recent and older relationships affect coinvestment performance. Here we find that it is the more recent history, not the older ones, which has a significant negative effect on IPOs and Exits.¹⁴ These findings are in line with the argument of Hypothesis 4B that performance declines first and is then followed by a gradual decline of coinvestments.

4.5. Robustness

In this section we examine the robustness of our results, focusing specifically on market trends and the fact that our analysis is limited to the top-100 VCs. Their investments involve more than half of all financing rounds and 68 % of all VCs in the population of VC investments made in the U.S. What is missing in our sample is the investments made amongst non-top VCs. To investigate whether these omitted investments affect our empirical predictions we consider four proxy measures for evolving market trends in general, and the market share of the top-100 VCs specifically. For this we calculate the total number of financing rounds made by all VCs in a year denoted by “Deals”, the total number of new investments made in a year by “New Deals”, and the total number of VCs making investments in a year by “VCs”, respectively. Because our base model already includes year fixed effect, the direct effect of these trend variables is already fully captured. However, we may still ask if these trends affect the strength of our main explanatory variable, i.e., the joint coinvestment history.

In Table 8 we report regressions including market trend proxies as interaction variables. In column (1), we interact our joint history variable with above-median and below-median dummy variables of “Deals” and obtain negative and significant coefficients for both interaction terms. An F-test of significance of differences between these two interaction terms reveals that such difference is not statistically significant (F-statistic=0). When we replace the overall market trend with the number of new investments in a year in column (2), we obtain similar predictions. We obtain negative and significant effects on both interaction terms while the difference between the two coefficients is not statistically significant (F-statistic=0.5). Column (3) further examines the number of active VCs in a year. The impact of joint history on the likelihood of co-investment remains negative and significant regardless of the number of active VCs making investments in a year. The F-statistic of 3.18* suggests that the negative impact of joint history is stronger when the number of active VCs is above sample median.

Next we turn to the role of the market share of the top-100 VCs. The proportion of financing rounds invested by the top-100 VCs, relative to the overall population of deals, varies over time. Their highest market share is 85 % in 1994, their lowest 55 % in 2012. To further investigate the role of market shares for the top-100 VCs, we interact the past syndication with below and above median of top VCs’ market shares in a year. Table 8 column (4) reports that regardless of the market share of the top VCs, the negative impact of past syndication on future syndication remains negative and significant. Stronger impact is present when the top VCs’ market share is below market median (F-statistic=3.20*). This lends support to the notion that VCs get more tired of their old partners when the market abounds with more investment opportunities.

¹³ The economic impacts are also significant: an increase of a standard deviation of the “Older-history” (1.19 coinvestments) can decrease the likelihood of them coinvesting in the future by 0.15%, equivalent to 30% of the average likelihood of coinvestment for the whole sample.

¹⁴ An increase of a standard deviation of the “Recent-history” (1.92 coinvestments in the sample of realized syndicates) can decrease the likelihood of an IPO and Exit by 2% and 3%, respectively.

Table 8

Market trend and market share. In this table, we interact past coinvestments with proxies for market trend and market share of top VCs. We dropped year fixed effects to allow main effects of market trend and market share variables in the regressions. All variables are defined in Table 1. All regressions apply the Linear Probability Model. Standard errors reported in parentheses are double-clustered at the VC-pair level and the company level. We use ***, **, and * to denote significance at the 1 %, 5 %, and 10 % levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable: Coinvestment				
Joint-history x Deals: <median	-0.056***			
	(0.010)			
Joint-history x Deals: >median	-0.057***			
	(0.010)			
Deals: >median	-0.041***			
	(0.011)			
Joint-history x New Deals: <median		-0.060***		
		(0.010)		
Joint-history x New Deals: >median		-0.053***		
		(0.010)		
New Deals: >median		-0.021**		
		(0.010)		
Joint-history x VCs: <median			-0.047***	
			(0.010)	
Joint-history x VCs: >median			-0.069***	
			(0.010)	
VCs: >median			-0.043***	
			(0.011)	
Joint-history x Market Share: <median				-0.066***
				(0.009)
Joint-history x Market Share: >median				-0.046***
				(0.011)
Market Share: >median				0.068***
				(0.010)
Deal FE/ VC-pair FE/ Controls	Yes	Yes	Yes	Yes
Observations	4,392,427	4,392,427	4,392,427	4,392,427
R-squared	0.195	0.195	0.195	0.195

To further examine the role of market shares, and to ensure that we do not give disproportionate weight to the largest VCs, we create a subsample for which we hold constant the proportion of financing rounds made by top VCs, relative to the population over the sample period. That is, we randomly drop deals made by the top-100 VCs so that the top-100 VCs' market share is held constant at 55 % every year – recall that 55 % is the lowest market share in our sample period. Using this subsample, we replicate several of our baseline regression. As shown in Table A.6 of the Online Appendix, we find that all of our main results continue to hold in this subsample. All of these robustness checks suggest that our focus on the top-100 VCs does not affect any of the core findings.¹⁵

¹⁵ The largest VCs in our sample are naturally part of more of the observations, so another potential concern is that our statistical analysis oversamples them. Our regressions already control for such sampling issues by using double-clustering of standard errors. Indeed, our base model clusters on company and VC pairs. To address the specific concern about oversampling larger VCs, we performed one more robustness check using an alternative clustering approach. Specifically, in an unreported regression (available upon request) we double-cluster the standard errors at the company (as before) and the *individual* VC level (instead of the VC pair level). The results are very similar, suggesting that the results are not affected by oversampling individual VCs.

4.6. Economic mechanisms

We propose that the underlying rationale for VCs to depart from their old partners is a substitution effect, where VCs are eager to pursue more investment opportunities with *other* VCs in the market. We thus examine whether a history of more coinvestments in the past leads to doing more coinvestments with *other* VCs going forward. To capture the coinvestments with other VCs, we define “Average Other Syndicated Deals” as the average number of rounds a pair of VCs have coinvested with other VCs (outside the pair) in the current quarter. Also, we define “Past-other syndicated deals” as the average number of rounds a pair of VCs have coinvested with other VCs (outside the pair) in the past five years. In column (1) of Table 9 we use “Average Other Syndicated Deals” as the dependent variable, to investigate whether past coinvestments of a pair of VCs affect the coinvestment with other VCs outside the pair. In column (1) of Table 9 we use “Past-other syndicated deals” as an additional control variable for our base model. This allows us to explore whether coinvestments with other VCs have any impact on current coinvestment of the pair of VCs.¹⁶

We report regression results in Table 9. In column (1) we find that having more past coinvestments increases VCs' tendency to coinvest more with other VCs. In column (2) we find that VC pairs coinvest more after having experienced more intense relationships with other VCs outside the pair. This additional evidence supports our Hypothesis 1 and suggests an economic mechanism based on substitution effects. Of particular importance is the notion that VCs have a fear of missing out. They continuously expand their networks, and spread their coinvestment across partners where the relationship is not as well developed.

5. Conclusion

This paper empirically examines a dynamic trade-off for managing investor relationships. In the fast-paced environment of VC, we show how VCs dynamically adjust their relationships to balance benefits of familiarity and trust against the opportunity costs of missing out on

Table 9

Patterns of substitution, In this table, we examine the conjecture that a history of more coinvestments in the past leads to doing more investments with other VCs going forward. In column (1), the dependent variable “Average Other Syndicated Deals” captures the average number of rounds a pair of VCs have coinvested with other VCs (outside the pair) in the current quarter. In column (2) the key independent variable is “Past-other syndicated deals” which measures the average number of rounds a pair of VCs have coinvested with other VCs (outside the pair) in the past five years. In this regression we drop “Experience-avg” in the controls due to its high correlation with “Past-other syndicated deals”.

	(1)	(2)
Dependent Variable:	Average Other Syndicated Deals	Coinvestment
Joint-history	0.039***	-0.062***
	(0.009)	(0.008)
Past-other syndicated deals		0.002***
		(0.000)
Deal FE/ VC Pair FE/Controls	Yes	Yes
Observations	4,392,427	4,392,427
R-squared	0.655	0.195

¹⁶ If a focal pair of VCs (call them VCA and VCB) have a strong history of past coinvestments and want to disengage from each other, then each VC is likely to increase its coinvestments with other non-focal VCs (e.g., VCA increases coinvestments with VCC, and VCB with VCD). The symmetry argument is that we should thus expect that if the focal VCs (VCA and VCB) have a strong history of past coinvestments with other partners (VCA with VCC and VCB with VCD) that they want to disengage from, then they are likely to increase their joint coinvestments (i.e., VCA with VCB).

alternative investments. Our results challenge the notion that partners always want to deepen relationships. Instead, we find they gradually retreat from overly deep relationships. We examine how network centrality and market settings affect these dynamic adjustments. Our framework also helps to explain why deeper relationships can lead to lower venture performance.

Our paper adds to the venture capital literature by focusing on the challenges of dynamically adjusting relationships over time. The analysis explains when investors want to increase or decrease the intensity of their interactions, how this depends on their positions in the network, and how it depends on external market conditions. The paper thus contributes to the VC finance literature, demonstrating the inherently dynamic nature of VC relationships. It addresses previously unexplored aspects of investment decisions made by VCs who constantly need to stay abreast of changing market opportunities. Finally, our methodology of using VC-pair fixed-effects helps to disentangle cross-sectional and longitudinal effects. This allows us to explain why VCs who may be ‘good friends’, can still ‘get tired of each other.’

Our findings open up numerous avenues for future research. Our analysis measures performance in terms of company exits, but ultimately one would like to measure the effect of relationships on investor returns. Another interesting question concerns the level at which relationships occur. Our data only allows us to examine relationships at the level of VC firms. Recent work by [Ewens and Rhodes-Kropf \(2015\)](#) notes that some of the effects in VC may occur at the level of VC partners instead of the VC firms. An interesting line of future research would thus be to look at how individual partners affect the dynamic relationships across VC firms.

Let us briefly point out the managerial relevance of the analysis. VCs constantly have to decide where to focus their limited time and money. Faced with a relentless flow of investment opportunities, they constantly face alternative investment choices that involve different sets of syndication partners. If a VC firm feels under- or over-exposed to a particular coinvestor relationship, it can dynamically manage the relationship up or down by making more or fewer new coinvestments with that partner. Given capacity constraints, forgoing coinvestments with some partners creates room to make more coinvestments with others. Our research question therefore addresses the delicate balancing act that VC firms face constantly. Entrepreneurs also benefit from understanding these investor dynamics, because they affect the process by which their investor syndicates are formed.

CRediT authorship contribution statement

Qianqian Du: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Thomas Hellmann:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Supplementary materials

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