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GETTING TIRED OF YOUR FRIENDS:
THE DYNAMICS OF VENTURE CAPITAL RELATIONSHIPS

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ABSTRACT

Does doing more deals together always strengthen investor relationships? Based on the relationships of the top 50 US venture capital firms, this paper focuses on the strengths of relationships and their dynamic evolution. Empirical estimates indicate that having a deeper relationship leads to fewer, not more future coinvestments. Moreover, deeper relationships lead to lower exit performance, even after controlling for endogeneity. Interestingly, deeper relationships first lead to lower performance, and subsequently lead to a slowdown in the relationship intensity. Relationship effects are more negative for VC firms with less central network positions, and for deals made in "hot" investment markets.

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A data appendix is available at http://www.nber.org/data-appendix/w26274

1. Introduction

A large finance and management literature finds that prior relationships increase the likelihood of engaging in joint undertakings and typically lead to better performance (Brander, Amit, and Antweiler, 2002; Sorenson and Stuart, 2008). Closely related is the large literature on networks that goes beyond the analysis of individual relationship pairs and looks at the overall architecture of a network of relationships (Hochberg, Ljungqvist, and Lu, 2007; and Cohen, Frazzini, and Malloy, 2008). A surprising limitation of this literature is that large parts of it rely on a simplistic characterization of what a prior relationship is, namely whether there is any prior joint activity or not. What gets overlooked is the quality of the relationship, and how relationships evolve over time. Do relationships always deepen? When do they weaken? Do deeper relationships always improve performance, or can they also hamper performance?

The US venture capital (VC henceforth) industry is well suited to study relationships because venture capitalists (VCs henceforth) frequently coinvest in deals, and because there are well-established VC firms that interact with each other over long horizons. Moreover, the structure of VC deals is well-suited for studying relationship dynamics, because of the relatively high frequency of transactions, both in terms of financing new companies and continuing to finance existing companies through several rounds. The central research questions for this paper are: How do VC relationships dynamically strengthen or weaken over time? How does the strength of these relationships affect performance? And how do market conditions affect this?

To answer these questions, we require a sufficiently long history of VC deals. This naturally leads us to Thomson One, which has the longest and most comprehensive coverage of VC deals in the US. We focus on the 50 largest US VC firms, analyzing all their coinvestment decisions over the period 1985 – 2012 (further following performance through 2016). For each of the 2450 (= 50*49) pairwise relationships formed by those top 50 VC firms we consider the set of potential coinvestment opportunities, identified as the set of investment rounds where at least one member of the pair invests. We identify over 1.4 million such coinvestment opportunities.

Our empirical analysis proceeds in three main steps. The first step establishes how the strength of past relationships affects the likelihood of further joint investment activity. Specifically, our empirical regressions estimate the determinants of new realized coinvestments, i.e., whether the two VCs actually coinvest or not in a round. The key independent variables relate to the prior history of the VC firms, both their individual histories as controls, and their joint histories which allow us to analyze the strength of prior relationships. The econometric model also includes numerous additional controls. Of particular importance are VC-pair fixed effects which absorb all cross-sectional variation across VC-pairs, and therefore focus the analysis exclusively on the dynamic evolution of relationships within a given VC-pair. In fact, we begin by demonstrating the importance of these fixed effects by showing how models with less powerful fixed effects (such as using none or using individual VC fixed effects only) suggest a positive effect of prior relationship strength on the likelihood of making another coinvestment. However, this effect turns out to be driven by the cross-sectional variation across VC-pairs. Once we remove that with our VC-pair fixed effects, we find that within a given VC-pair, there is a negative relationship between prior relationship strength and the likelihood of making another coinvestment. At first this result may come as a surprise, as the prior literature might leave the impression that better relationships should lead to further coinvestments. The fact that we find the opposite suggests that there are countervailing forces that over time weaken stronger (and strengthen weaker) relationships. Hence the paper's title is about "getting tired of your friends".

The second step of our empirical analysis considers the performance implications of relationship strength. We look at the correlation of our relationship measures with the likelihood that an investment results in an exit. In the absence of returns data, exits in terms of IPOs and acquisitions are the standard measure of performance in the VC literature (see Da Rin, Hellmann, and Puri, 2012; Phalippou and Gottschalg, 2009). We find that stronger prior relationships are negatively correlated with exit rates. Naturally there is an endogeneity question whether this finding could be driven by selection effects. For example, VCs with stronger prior relationships might choose less promising entrepreneurial companies. We use the Heckman (1979) two-step procedure to address this concern where the first stage looks at coinvestment formation and the second stage at investment performance.[1] To identify the Heckman model, we use two 'instrument-like' variables that are included in the first stage but not the second stage. The first variable captures the overlap in investment markets of the VC-pair. The key idea is that exogenous increases in the areas of interest are likely to bring VCs closer to each other. The second variable is based on the VCs' indirect partners, defined as those coinvestors who are not in the set of overlapping coinvestment partners of the two VCs. The idea is that indirect partners demand attention from a VC and therefore divert his attention from investing in the focal coinvestment partner. Because the indirect partners are not part of the focal deal, they don't have a direct impact on performance for the second stage. However, we show that they have high predictive power in the first stage. Importantly, we find that even after the Heckman procedure, the key dependent variable about prior relationships remains significant in the second stage regression. Thus the

[1] The Heckman two-step procedure has been widely used in the corporate finance literature. See Bris, Welch and Zhu (2005), Campa and Kedia (2002), and Villalonga and Amit (2006).

negative effect of prior relationships on exit performance does not appear to be driven by selection effects.

The third step of our empirical analysis consists of identifying mechanisms that can explain the two core findings about stronger relationships weakening over time and leading to weaker exit performance. For this step we consider three additional empirical tests.

First, we consider the longevity of relationship effects. Do joint activities in the recent past matter more than those in the more distant past? For this we decompose our 5-year running horizon used in the main specification into two subperiods, the recent past (the last 2 years) versus the more distant past (the last 3 to 5 years). Interestingly, we find that the recent past has a positive effect on new coinvestment, but that the more distant past has a (stronger) negative effect. We also perform numerous other ways of measuring the recent versus more distant past and find a consistent message across all the specifications. This finding is consistent with the notion of "getting tired of your friends". Over shorter horizons there is a self-reinforcing aspect to relationships, but over the medium term there is a reversion effect where VCs loosen those relationships that may have become too tight. We also consider the effect of younger versus older relationships on exit performance and find that the negative effect of stronger relationships is concentrated in the recent past. Together, these results suggest that as relationships get deeper, they first lead to a deterioration of performance, and then lead to a loosening of the relationship.

Second, we consider how market conditions affect the strength of relationships. The VC industry is known for its wild cyclical swings (see Gompers and Lerner, 1999). It has "hot" market periods where investments are abundant and the mood euphoric (the dotcom boom of 1998 to early 2001 being the most notable episode), and "cold" market period where investments slow down considerably, and the mood is more cautious (such as the dotcom bust of 2001 to 2004). We consider whether relationships formed in hot markets have a different quality than those formed in cold markets. Indeed, we find that the negative effect of prior relationships on current coinvestment behavior stems from hot market relationships. The analogy of this in interpersonal relationships would be that friendships forged in hard times (e.g., “wartime friends”) are stronger than those forged in easy times (e.g., “party friends”).

Lastly, we ask whether there is a trade-off between relationship depth and network position? While our focus is on the dynamics of the relationships between a pair of VCs, a VC’s network position captures its connection to all other VCs in the market. We find that VCs well-connected in the network are more likely to maintain their relationships with other investment partners. Similar to the prior literature (Hochberg, Ljungqvist, and Lu, 2007), network centrality is also associated with better venture performance. Furthermore, we find that network centrality moderates the negative impact of past coinvestments on future coinvestments, i.e., the negative impact of past coinvestments is weaker for pairs of VCs that are more central in the network.

Overall this paper challenges the received wisdom that deeper relationships are always beneficial. Instead we find that deeper relationships lead to lower exit performance over the near term, and a retrenchment from relationships over the medium term.

Our paper draws on several prior literatures. To begin with, there is a finance literature concerning the rationale for coinvestment. Early work by Brander, Antweiler and Amit (2002) finds that pooling of information and expertise dominates any concerns about adverse selection. The work of Du (2016) and Hochberg, Lindsey, and Westerfield (2015) emphasize how positive assortative matching and resource sharing affect the likelihood of forming a VC syndicate. The work of Casamatta and Haritchabalet (2007) considers the possibility of anti-competitive collusion. Morrison et al. (2018) examine the longevity and strength of investment banking relationships. In this context we should also mention several works of Gompers with co-authors (Gompers, Xuan, and Mukharlyamov, 2012; Gompers and Wang, 2017; and Gompers and Kovvali, 2018) which establishes in different contexts the importance of diversity in venture capital investment decisions. A recent review paper by Nanda and Rhodes-Kropf (2018) further discusses several possible causes for frictions within VC syndicates.

Outside of finance there is naturally a burgeoning literature on relationships and networks. The work of Sorenson and Stuart (2001, 2008) established the study of coinvestments as a basis for measuring social networks in venture capital. The work of Burt (2000), Dahlander and McFarland (2013), and Elfenbein and Zenger (2013) focuses on the longevity of network ties. Although much of the organization literature emphasizes the role of prior relationships in fostering future collaborations, a recent paper by Zhelyazkov and Gulati (2016) examines the consequences of tie dissolution on future tie formation. They find that the withdrawals made by VCs make them less desirable, not only to their prior coinvestors they withdraw from, but also to other potential coinvestors. Related to this, there is also a game-theoretic economics literature that looks at the strengths of reciprocal cooperative relationships (see Abdulkadiroglu and Bagwell, 2013; Berg, Dickhaut, and McCabe, 1995).

Our paper is organized as follows: Section 2 presents the hypothesis development; Section 3 shows how we construct our sample and define our variables; Section 4 provides regression results; Sections 5 and 6 report further empirical analysis and robustness checks. We conclude in Section 7.

2. Hypotheses on the dynamics of relationships

In this section we briefly develop some theoretical understanding of how past relationships map into current relationships. In principle there is a wide range of arguments that affect relationships, including interpersonal aspects, changes in the external environment, and many other factors. Our aim here is not to produce an exhaustive list of these factors, but rather to briefly consider the dynamic implications of how positive and negative relationship effects accumulate over time.

Consider a simple formalization with two VC firms, indexed with i and j. Their vector of past coinvestments is denoted by $\mathbf{x}(i,j)$. We are interested in the effect of this vector on the probability of a coinvestment for a given current deal. This probability is affected by a set of shocks, denoted by ε_i, ε_j, (pertaining to each individual VC) and ε_{ij} (pertaining to the specific VC pair). The utility of making a coinvestment for VC i is given by $U_i = f(\mathbf{x}) + \varepsilon_i + \varepsilon_{ij}$; similar for VC j. A coinvestment thus occurs whenever $U_i \geq 0$ & $U_j \geq 0$. The main question of interest concerns the shape of the $f(\mathbf{x})$ function.

Consider first the null hypothesis that relationships do not matter, i.e., that all coinvestments decisions are made independent of coinvestment histories. In this case the null hypothesis is simply $df(\mathbf{x})/d\mathbf{x} = 0$ for all elements of $\mathbf{x}$. We can contrast this against the conventional hypothesis that having a prior relationship always increases the probability in making coinvestments. This hypothesis implies that $df(\mathbf{x})/d\mathbf{x} > 0$ for all "relevant" components of $\mathbf{x}$. An alternative more nuanced hypothesis is that some types of prior deals strengthen the relationship, whereas others weaken them. In this case we have $df(\mathbf{x})/d\mathbf{x} > 0$ for some components of $\mathbf{x}$, $df(\mathbf{x})/d\mathbf{x} <0$ for others. The key empirical question becomes which components have a positive or negative sign. One can further refine this hypothesis to allow the effects of $\mathbf{x}$ to vary with external circumstances, to change over time, and so on.

It is worth drawing one important logical conclusion from this simple formalization. If the first hypothesis ($df(\mathbf{x})/d\mathbf{x} > 0$) is always true, then relationships only strengthen over time. This means that partners with a stronger relationship coinvest an increasing fraction of their deals with each other. This predicts that the portfolio of VC coinvestment relationships becomes increasingly concentrated. However, Figure D.1 from the Online Appendix suggests the opposite. We calculate the Herfindahl Index (HHI) to proxy for the concentration ratio of a VC's portfolio of partners. This measure is based on the percentage of deals coinvested with a specific partner, relative to the deals coinvested with all partners in a year. We report both the mean and median HHI of all top 50 VCs between 1990 and 2012 on the vertical axis, and the calendar year on the horizontal axis. We find that concentration ratios initially decreased, due to the entry of new VC firms early in the sample period, and then remained stable throughout the rest of the sample period. This is not consistent with the notion of ever-increasing relationship strengths. This casts some doubt about the conventional hypothesis, and thus points in the direction of the alternative more nuanced hypothesis that admits both positive and negative effects of prior coinvestment histories. This realization provides a starting point for our empirical analysis.

3. Data

3.1 Sample

We obtain the data of venture capital investments made in the US from the Thomson One database, formerly known as VentureXpert database or Venture Economics, which provides the most comprehensive coverage of US VC investment activities. While our original sample of venture capital investments starts in 1985, we use the first five years of the investment data to construct a VC's past experience and coinvestment relationships. Therefore, our sample used for the empirical analysis starts in 1990. Although our sample of venture capital investments ends in 2012, the information regarding the portfolio companies' IPOs and acquisitions is extended to the year of 2016. We require that the portfolio companies have at least four years of development before their performances are evaluated.[2] Our company sample consists of those companies that received one or more investments from at least one of the top 50 VCs which are listed in the Appendix B of the Online Appendix. This includes 8,389 companies, receiving a total of 30,061 rounds.

We focus on the relationships among top 50 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 50 firms keeps our sample size manageable at approximately 1.42 million observations. To identify the top 50 VCs, we require that a top VC firm started making venture capital investments before 2002, ensuring that it has invested for at least 10 years in our sample. We identify the top 50 on the basis of their number of rounds invested per year.

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 50 VCs who invest in the current round, or who invested in any of the previous company rounds. We call them "involved" since they either actually

[2] 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.

invest in the round, or clearly have the option to do so. We define the rest of the top 50 VCs as "not involved VCs". For each round there are in principle 2450 (=50*49) VCs 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 1225. 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 doesn't reveal much about their relationship, it simply says that neither consider the deal involved. This leaves us with a final sample of 1,420,945 VC-pairs involved in a company-round. The VC-pair-in-company-round is thus the unit of observation for our main empirical sample.[3]

3.2 Variables

All variables are defined in Table 1. We report our sample statistics in Table 2. Table 3 reports the correlation matrix of key variables. 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 could reasonably be expected to coinvest in a deal, actually do. Among the total of 1,420,945 observations, 0.68% of them are realized coinvestments made by VC-pairs in the financing rounds.

Our key independent "Past-coinvestments" measures the relationship history of two VCs based on the number of coinvestments they made in the past five years. On average, there are 2.81 past coinvestments made by any pair of VCs in the past five years. If two VCs have already

[3] We plot the distribution of the number of all possible coinvestments formed by all pairs of VCs from our top 50 list in Figure D.2 in the Online Appendix. The average (median) number of possible coinvestments formed by VC pairs is 579 (546). We further calculate the percentage of coinvestments that are realized and report it in Figure D.3. Realized investments represent an average (median) of 0.62% (0.36%) of all potential coinvestments.

invested in a specific company, and now face a new round, we should not be too surprised to find another coinvestment. The variable "Same-company" equals one if both VCs already invested in an earlier round of the company before the current round. While this only occurs in 0.01% of all observations, we find that conditional on having made a coinvestment in an earlier round, 56% of follow-up rounds in the same company result in another coinvestment. This suggests that there are strong norms around following up with coinvestments within the same company. Not surprisingly we consistently find that the "Same-company" variable is a powerful control.

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 versus more distant years, as well as past relationships made in hot or cold market. In Table 2, there are more coinvestments made in earlier years: VCs on average coinvest in 1.63 rounds in earlier years, compared with 1.18 rounds in more recent years. Regarding VCs' past coinvestments in hot and cold markets: there are an average 1.80 coinvested financing rounds made in hot markets and 1.01 coinvested financing rounds made in cold markets. Among all observations in our sample, 75% of current coinvestments are made in hot markets. Lastly, we capture the network position of a VC among all VCs in a market. We find the VCs in our sample are well-connected. For example, a VC on average coinvests with 11 other VCs in a five-year rolling window.

The variables discussed so far vary at the level of the VC-pair-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. As a robustness check we further add the differences between the two variables. The average number of financing rounds invested by a pair of VCs in the past five years is 164. 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. The average industry match of the two VCs is 0.3, suggesting 30% 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 0.31, suggesting 31% 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 venture capital literature (see Da Rin et al. 2012), we measure performance in terms of either IPOs or Exits (which include IPOs and successful acquisitions). 21% of the observations result in IPOs, and 52% of them in Exits. These variables will be used as dependent variables.

The companies financed by the top 50 VCs raise on average $14.66 million per round. The average time difference between a company’s founding date and the date of the first VC round is 4 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 (11%). In terms of stages, 8% are seed stage rounds, 24% early stage, 40% expansion stage, and 29% late stage.

4. Empirical estimation

4.1. Base model

Throughout the paper we use linear probability models (and later Heckman two-stage models). This is necessitated by the large number of observations and a large set of fixed effects used in all of our regressions (Wooldridge, 2007). In all regressions all standard errors are double-clustered at the VC-pair level and the company level.

The purpose of Table 4 is to explain the construction of our base model, and demonstrate the importance of certain controls, especially 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 "Past-coinvestments" and "Same-company" as two independent variables. "Past-coinvestments" 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. "Same-company" has a large positive and highly significant impact on "Coinvestment". This says that VCs tend to continue to invest in the company if they already financed the earlier rounds of the company.

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 all of these variables 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 4, 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 strikingly different prediction of “Past-coinvestments”. For a given pair of VCs, the more often they coinvested in the past, the less likely they will coinvest in the current round. The economic magnitude of the coefficient is meaningful. An increase of a standard deviation of the “Past-coinvestments” in the past five years (4.54 coinvestments) can decrease the likelihood of them syndicating in the future by 0.09%, equivalent to 13% of the average likelihood of coinvestment for the whole sample (0.68%).

The striking difference between Column (3) and (4) suggests that the dynamics of relationships is entirely different if examined among all VCs in a pooled regression or for a given pair of VCs in regressions with pair fixed effects. Without pair fixed effects, the estimation of “Past-coinvestments” may be biased due to the omitted characteristics of the pair which may also correlate with the “Past-coinvestments” of the VC pair. One example of the omitted characteristics is the outside options faced by the pair of VCs. According to Greve, Mitsuhashi, and Baum (2013), the availability of promising partners outside the alliances may lead to alliance withdrawals from existing alliance partners, enabling them to pursue better matches in the future. This illustrates the importance of controlling for VC-pair fixed effects when studying a VC’s choice of coinvestors. Therefore, unless otherwise specified, we use VC-pair fixed effects for the remainder of the analysis.

4.2. Exit performance

If past coinvestments affect the likelihood of VCs coinvesting in the future, do they also matter for the VCs' investment performance? To evaluate the investment performance, we follow the prior venture capital 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 multi-variate correlations. We discuss endogeneity in Section 4.3. The empirical results are presented in Table 5. Because the performance is only observed for realized coinvestments, all regressions are based on the subsample of realized coinvested deals. Column (1) reports the regression results when the performance proxy is IPO. We find that for a given pair of VCs, their Past-coinvestments are negatively associated with having an IPO. In Column (2) of Table 5, we use Exit as an alternative measure of investment performance. The results are very similar to those in Column (1). Combined with our baseline regression results reported in Column (4) of Table 4, past coinvestments not only decrease the likelihood of future coinvestments but also the likelihood of future success.

4.3. Endogeneity

Table 5 does not establish a causal relationship between the past coinvestments and venture success, instead it only shows the correlations between the two variables. The next step is thus to address endogeneity. A common concern in the venture capital literature is that performance effect may be due to selection effects. In our context, the question is whether better companies attract VCs with fewer past coinvestments. To address this question we use the Heckman two-step approach. In the first step, we examine how VCs select each other to coinvest in a particular company round. In the second step, conditioning on their investments, we examine how a pair of VCs' past-coinvestments affect the success of their coinvested company. To satisfy the 'exclusion restrictions' of the Heckman model, we develop two variables that work in a similar fashion to instrumental variables in a two-stage least squares model.[4] Specifically, they directly affect the likelihood of coinvesting but (based on any existing theory or industry evidence) should not have a direct impact on the venture success.

The first instrument is called "Common-markets". For this we count the number of overlapped markets a pair of VCs have invested in the past 12 months. The number of overlapped markets mainly captures whether there are any common interests shared by the pair of VCs. Therefore, it is different from the number of coinvested deals, which captures the extent of intensity of coinvestments made by the VCs in a pair. To develop this instrument, we first define a market as the interaction between a state and an industry, e.g., the market for computer-related deals in California. We then code the markets that both VCs have invested in the past 12 months and count the number of these markets. The logic for this instrument is as follows. If two VCs have more overlaps in the markets of their investment targets, it is more likely that they meet each other more often and eventually collaborate their coinvestments. On the other hand, the extent of market overlaps in the past should not have a direct impact on the success of the deal they are currently investing in, especially given our strong fixed effects that already control for industry, state, time, and even VC-pairs.

The second instrument is "Indirect-partners" which captures the number of indirect partners a VC pair has in the past five years. For a given pair of VCs, a focal VC's indirect partners are his coinvestment partner's coinvestment partners, but only those who did not coinvest with the focal VC himself in the past. For a detailed illustration, please refer to the Appendix E in the Online

[4] Usually the term 'exclusion restriction' is associated with instrumental variables, but we use it here too. This is because of the similarly of structure that our 'instrument-like' variables are only used in the first stage, but not the second stage.

Appendix. The logic of this instrument is as follows. On the one hand, there exists no investment relationship between VCs and their indirect partners. As a result, we should not expect VCs' indirect partners could directly influence the VCs' investment performance. On the other hand, the remote network of partners affects the investments of the focal VC's partners. In particular it can distract them, so that the focal VC's partners invest their limited funds with the indirect partners instead of with the focal VCs. Consequently we predict that the indirect partners will have a negative impact on the likelihood of the two VCs coinvesting in the first stage. Moreover, in the second stage the indirect partners do not affect performance since they are not actually part of the investment at all, thus satisfying the 'exclusion restriction'.

Table 6 reports the results of the Heckman model. Column (1) reports the regression results of the first stage and Columns (2) and (3) report the second stage[5]. For the first stage, our two instruments have expected impacts on "Coinvestment". In the second stage, we continue to find the negative impact of "Past-coinvestments" on venture success proxied by IPO in Column (2). When Exit is used to proxy for venture success, we find the same prediction in Column (3). Based on the F-test, the two instruments are jointly significant at the 1% level (the Chi-square statistic is 47.17 for both IPO and EXIT regressions). In addition, the Lamda of Heckman models is positive but not significant, suggesting that the unobserved selection between the VC pairs and the invested company is not the driving force of results.

5. Breaking out the effect of past coinvestments

[5] The original Heckman two-step procedure does not have a fixed effects option in STATA. We therefore manually added the dummies of VC-pairs in the regressions. Adding these dummies requires much greater computational power. To run Heckman with the pair fixed effects, we have to drop those VC pairs who never coinvest in our sample and drop dummies of company state and round number from the Deal-FE.

In this section we consider additional empirical analysis to uncover some of the mechanisms behind our main findings that more coinvestments in the past can lead to fewer coinvestment in the future, and to lower exit performance. For this we consider several breakdowns of our main independent relationship variable. We first distinguish between younger versus older relationships; we then distinguish between relationships forged in hot versus cold markets; finally we consider the interaction with network centrality.

5.1. Younger versus older relationships

We first decompose the relationships into younger coinvestments and older coinvestments and examine which types of relationships matter more. Table 7 reports the empirical results. Suppose a pair of VCs are considering coinvesting at time t=0, younger coinvestments are those they formed in years t=-1 and t=-2 while older coinvestments are those formed in t=-3 through t=-5. As shown in Column (1) of Table 7, coinvestments formed fairly recently, denoted by "Younger-coinvestments," have a positive and significant impact on future coinvestments. However, coinvestments formed in earlier years, denoted by "Older-coinvestments", have a negative and significant impact on future coinvestments. The empirical results suggest that the negative impact of the past coinvestments on future coinvestments is mainly caused by the older relationships, not the more recent ones. That is, VCs are getting tired of their older friends, not their latest friends. Put differently, it takes several years before the effect of "getting tired" kicks in.

In Column (2), we further examine how younger and older relationships would affect venture success proxied by IPO. We find that younger coinvestments, instead of older coinvestments are associated with lower IPO rates. Column (3) replaces IPO with Exit and we continue to find the negative impact of past coinvestments on Exit comes from younger relationships. This suggest an interesting interpretation that the negative effect of deeper relationships have a fairly rapid effect on venture performance. However, it takes VC firms longer to step away from these less productive relationships.

5.2 Hot versus cold markets

Because venture capital investments are highly cyclical, we further decompose past relationships into the coinvestments made in hot times and in cold times and examine how they affect the future coinvestments and venture success. We first construct markets by interacting every quarter with every industry and calculate the dollar amount invested in each market.[6] We define a market 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 define the rest as cold markets. Table 8 Panel A reports how venture market conditions affect future coinvestments. Starting with Table 8, we will not report the coefficients of all the control variables for brevity, but we use the same set of controls as our baseline model reported in Column (4) of Table 4. Column (1) shows that while past coinvestments made in hot markets have a negative and significant impact on future coinvestments, past coinvestments made in cold markets have an opposite positive impact. This suggests that the negative impact of past coinvestments from our baseline model is mainly caused by the past coinvestments made in the hot markets. Relationships built in good times when the market has plenty of investment opportunities are less likely to sustain in the long run. However, relationships formed in bad times when investment opportunities are rarer are more likely to be maintained overtime. The investment relationships formed in bad times provide the evidence of reciprocity in

[6] Note this this definition of market is slightly different than the definition of common markets used in section 4.3, which also includes a geographic element. This geographic element is less important for the definition of hot versus cold markets.

VC investments.[7] Our findings echo with a saying about interpersonal relationships that "a friend in need is a friend indeed."

In Column (2), we define hot or cold markets based on the current investments, that is, whether the current investment is made in a hot or cold market. The regression results suggest past coinvestments have a negative and significant impact for current investments in a hot market while the impact of past coinvestments is not statistically significant for current investments in a cold market. In the next step, we interact the past coinvestments in a hot or cold market with the current investment in a hot or cold market and examine how they affect the likelihood of current coinvestments. We report the results in Column (3): past coinvestments made in hot markets have a negative and significant impact on current investments, no matter whether made in currently hot or cold markets. However, past coinvestments made in cold markets have a positive and significant impact on coinvestments in currently cold markets. This reflects the nature of reciprocity in sustained relationships: if firms helped each other during bad times, once they survive in the future, they will continue to help each other if bad times happen again.

In Panel B, we report how the interaction of hot and cold markets between the past and the current investments affects venture success. In Column (1) where IPO is used to proxy for success, we find that past coinvestments made in hot markets have a negative and significant impact on future IPO rates, irrespective of whether the current markets are hot or cold. If we replace IPO with Exit in Column (2), we still find a negative impact on exit rates when VCs with past relationships made in hot market make investments in cold markets. We do not find any significant impact of past coinvestments made in cold markets on future exit rates.

[7] This is consistent with the favors that are reciprocated by self-interested players in a model with repeated interactions with private information by Abdulkadiroglu and Bagwell (2013).

5.3 Relationships versus network

Although our focus is to explore the dynamics of relationships within a pair of VCs, we also examine whether a VC's position in a broader investor network plays any role in our results. To capture a VC's network position, we follow the literature and use the degree centrality of a VC, that is, the number of unique coinvestment partners a VC has in the past five years. We further normalize this measure by the maximum number of coinvestment partners a VC could possibly have in the past five years. We first examine whether the average degree centrality of a pair of VCs has any impact on coinvestments in Table 9 Panel A. In Column (1), we find that, the more connected the pair of VCs are, the more likely they will coinvest in the future. In Column (2), we add our key independent variable Past-coinvestments between a pair of VCs and still obtain a negative and significant impact on future coinvestments. We then interact the two network variables in Column (3) and obtain a positive and significant coefficient of the interaction term, suggesting that for VCs that are well-connected in the investor network, past relationships are more likely to sustain in the long run. Although VCs in general can get tired of their old friends, they do less so if they are more central in the investment community.

In Panel B, we further examine whether a VC's network position has any impact on venture performance. We find a positive impact of the average degree centrality of VCs on venture success, mostly significant at the 10% level (except in column 2). This result is in line with the prior literature (Hochberg et al., 2007). However, the addition of a network centrality measure has no discernible effect of past coinvestments, our main variable of interest. Moreover, the interaction term of past coinvestments with degree centrality is insignificant, as shown in columns (2) and (4). This suggests that the effect of past coinvestments on exit performance operates independently of any concerns about network centrality.

6. Robustness

6.1 Non-linear relationship

In this section we examine whether the negative impact of past-coinvestments is linear. We report all of the regression results of robustness checks in the Online Appendix. In Panel A of Table A.1, we report regressions based on the squared and cubed terms of past-coinvestments. While we find the evidence of a convex relationship between past-coinvestments and current coinvestments, the magnitude is very small as shown in Column (2) and (3). In Panel B, we further examine whether there is any nonlinearity present in regressions of venture success. Overall speaking, the results do not support a robust nonlinear effect of past-coinvestments on IPO and EXIT.

6.2 Alternative definition of Past-coinvestments

We define Past-coinvestments based on the number of rounds a pair of VCs have coinvested in all other companies in the past five years. As an alternative, we define a relative measure "Past-coinvestments%" for which we scale Past-coinvestments by the number of potential coinvestments a pair of VCs could possibly have in the past five years. The potential coinvestments are defined in session 3.1 and the results are reported in Table A.2. Column (1) suggests that higher percentage of Past-coinvestments is negatively associated with the current coinvestments, consistent with our baseline findings. In addition, companies financed by VCs with higher percentage of Past-coinvestments are less likely to have IPO or EXIT in the future, as shown in Column (2) and (3).

6.3 Add VC-year fixed effects

In prior regressions, we control for VC-pair fixed effects to capture all observable and unobservable time-constant characteristics of the pair of VCs. Therefore, our results are unlikely to be biased by variables that are defined at the VC-pair level. In this session, we further control for time-varying characteristics of VCs to capture all observable and unobservable characteristics of individual VC firms over time. It is possible that the tendency to coinvest changes as VCs improve their deal selection ability or experience changes in their investment focus and strategies over time. In Table A.3, we report regressions including the VC-Year fixed effects for both coinvesting VCs. In Column (1), we continue to find a negative impact of Past-coinvestments on VCs' future coinvestments. Meanwhile, Column (2) and (3) report that companies financed by VCs with more Past-coinvestments are less likely to have an IPO or EXIT in the future, consistent with our baseline results.

6.4 The differences between VCs

One important reason that drives coinvestment is the sorting among VCs based on different VC characteristics. In our research context, a positive sorting suggests VCs that are similar for certain characteristics are more likely to coinvest while a negative sorting suggests VCs that are different for certain characteristics are more likely to coinvest. To formally test which type of sorting prevails, we construct variables that capture the difference between VCs in their general experience denoted by "Experience-diff", industry fitness denoted by "Industry-diff", state fitness denoted by "State-diff", and stage fitness denoted by "Stage-diff". In Column (1) of Table A.4, we control for the four types of difference variables and our prediction remains consistent with that in the baseline regressions. In addition, we find evidence supporting a positive assortative matching among VCs, that is, VCs with different levels of general experience, industry fitness, and state fitness are less likely to coinvest. In Column (2) and (3), after controlling the difference variables, we still find consistent results to our baseline regressions.

7. Conclusion

This paper challenges the received wisdom that deeper relationships are always better relationships. Once we include VC-pair fixed effects into the analysis, we find that higher levels of past coinvestment activity leads to fewer, not more new coinvestments. Moreover, higher levels of past coinvestment lead to lower exit performance, a result that continues to hold after controlling for endogeneity. The empirical analysis suggests that the negative performance effect of deeper relationships comes first, followed by a somewhat slower retrenchment from deeper relationships. Retrenchment from deeper relationships is also stronger when these relationships were mostly established in hot markets. VC firms with lower network centrality also exhibit stronger retrenchment.

Our findings about the negative effects of relationships also challenge some of the received wisdom that tends to merely think of relationships as assets not liabilities. Our findings suggest some interesting avenues for future research. We examine relationships at the level of VC firms. Recent work by Ewens and Rhodes-Kropf (2015) notes that some of the effects in venture capital may occur at the level of VC partners instead of the VC firms. Their analysis depends on tracking the movement of partners across VC firms. The work of Gompers, Xuan, and Mukharlyamov (2012) and Gompers and Wang (2017) further suggests that interpersonal ties between VC partners from similar ethnicities and educational backgrounds matter. An interesting extension would thus be to look at how these partner level effects affect the dynamic relationship effects identified here.

Another important set of questions concern the underlying motives that explains the (relative fast) decline in exit performance and the (slightly slower) retrenchment from deeper relationships. There can be numerous conjectures here: do VC firms' investment interests merely diverge over time? Do they seek to strategically differentiate from each other? Or is there actual dissatisfaction with the coinvestment partners themselves? Future research might gather additional data on the investment strategies of VC firms to disentangle some of these alternative conjectures.

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Table 1: Variable definitions

Variable	**Definition**
VC-pair-company-round level:	
Common-markets	The number of overlapped markets VCi and VCj have in the past 12 months. The market is defined as the interaction between the state and industry of a portfolio company.
Degree-avg	It calculates the average degree centrality of the two VCs in a pair. The degree centrality captures the number of unique coinvestment partners a VC has in a rolling five-year window. To make this measure comparable across years, in the regressions, we normalize the degree centrality by the maximum number of syndication partners a VC could possibly have in every five-year window.
Experience-avg	For each VC-pair-company-round observation, it is the log of 1 plus the average experience of VC*i* and VC*j*. Experience is the number of rounds a VC has invested in the past five years.
Indirect-partners	The total number of indirect partners VC*i* and VC*j* have in the past 5 years. A VC's indirect partner is defined as this VC's coinvestment partner's coinvestment partner which has never coinvested with the VC in question before.
Industry-avg	For each VC-pair-company-round observation, it is the average industry match value of VC*i* and VC*j*. Industry match value is defined as the percentage of rounds a VC has invested in the company's industry in the past five years.
Older-coinvestments	For each VC-pair-company-round observation in year t=0, it is the number of coinvested rounds by the VCs in years t=-3 through t=-5.
Past-coinvestments	The number of rounds that VC*i* and VC*j* have coinvested in all other companies in the past five years.
Past-hot-coinvestments / Past-cold-coinvestments	The number of rounds that VC*i* and VC*j* have coinvested in all other companies in hot/cold markets in the past five years. We first construct markets by interacting every quarter with every industry of a portfolio company and calculate the dollar amount invested in each market. We 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 define the rest as cold markets.
Same-company	A dummy variable, which indicate whether the pair of VCs in the current round have coinvested in an earlier round of the same company.

Stage-avg	For each VC-pair-company-round observation, it is the average stage match value of VC*i* and VC*j*. Stage match value is defined as the percentage of rounds a VC has invested in the company's stage in the past five years.
State-avg	For each VC-pair-company-round observation, it is the average geographic match value between VC*i* and VC*j*. Geographic match value is defined as the percentage of rounds a VC has invested in the company's state in the past five years.
Younger-coinvestments	For each VC-pair-company-round observation in year t=0, it is the number of coinvested rounds made by the VCs in years t=-1 and t=-2.
Company round level:	
Coinvestment	A dummy variable, which is equal to 1 if a pair of VCs coinvest at the current financing round, and 0 otherwise. It is multiplied by 100 when we use it as the dependent variable in the regressions.
Now-hot / Now-cold	A dummy variable, which is equal to 1 if the current investment is made in a hot/cold market. We first construct markets by interacting every quarter with every industry and calculate the dollar amount invested in each market. We 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 define the rest as cold markets.
Round-amount	It captures the amount of investment provided to a financing round. We use the log of the Round-amount in regressions.
Company level:	
Company-age	Age of the portfolio company, which is calculated as the number of years between the year when it is founded 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, 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.
***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, 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	1420945	0.68	8.23	0.00	0.00	0.00
Past-coinvestments	1420945	2.81	4.54	0.00	1.00	12.00
Same-company	1420945	0.01	0.08	0.00	0.00	0.00
Experience-avg	1420945	163.54	62.96	64.50	158.50	275.00
Industry-avg	1420945	0.30	0.18	0.05	0.28	0.61
State-avg	1420945	0.34	0.26	0.01	0.37	0.75
Stage-avg	1420945	0.31	0.12	0.12	0.31	0.49
Round-amount	1420945	14.66	25.07	0.80	9.00	46.02
Company-age	1420945	4.12	4.32	0.00	3.00	11.00
Common-market	1420945	4.43	2.64	1.00	4.00	9.00
Indirect- partners	1420937	0.46	0.08	0.31	0.47	0.55
Exit	1420945	0.52	0.50	0.00	1.00	1.00
IPO	1420945	0.21	0.41	0.00	0.00	1.00
Younger-coinvestments	1420945	1.18	2.07	0.00	0.00	5.00
Older-coinvestments	1420945	1.63	2.90	0.00	0.00	7.00
Past-hot-coinvestments	1420945	1.80	3.22	0.00	0.00	8.00
Past-cold-coinvestments	1420945	1.01	2.66	0.00	0.00	5.00
Now-hot	1420945	0.75	0.43	0.00	1.00	1.00
Degree-avg	1420945	11.48	4.37	6.08	10.74	19.78
No. of obs. by industry:						
Industry	Observations	Percent				
Biotechnology	138,859	9.77				
Communications and Media	266,115	18.73				
Computer Related	638,766	44.95				
Medical/Health/Life Science	158,578	11.16				
Non-High-Technology	87,068	6.13				
Semiconductors/Other Electronics	131,559	9.26				
Total	1,420,945	100.00				
No. of obs. by company stage:						
Stage	Observations	Percent				
Seed	115,351	8.12				
Early Stage	334,073	23.51				
Expansion	562,594	39.59				
Later Stage	408,927	28.78				
Total	1,420,945	100.00				

Table 3: Correlation matrix of main variables

We report the correlation matrix of key variables based on the sample of 1,420,945 VC-pair-company-round observations between 1990 and 2012. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Variable Name	No.	1	2	3	4	5	6	7	8	9
Coinvestment	1	1.00								
Exit	2	0.01***	1.00							
IPO	3	0.02***	0.50***	1.00						
Past-coinvestments	4	0.07***	0.01***	0.01***	1.00					
Past-hot-coinvestments	5	0.05***	-0.01***	-0.03***	0.83***	1.00				
Past-cold-coinvestments	6	0.05***	0.03***	0.07***	0.62***	0.08***	1.00			
Younger-coinvestments	7	0.06***	0.00***	0.01***	0.80***	0.67***	0.49***	1.00		
Older-coinvestments	8	0.06***	0.02***	0.01***	0.93***	0.77***	0.59***	0.53***	1.00	
Degree-avg	11	0.04***	0.05***	0.09***	0.41***	0.16***	0.50***	0.28***	0.41***	1.00

Table 4: Baseline models

The sample includes 1,420,945 VC-pair-company-round observations between 1990 and 2012. The dependent variable is a dummy variable to indicate whether the VC-pair coinvests in the current round. The rest of the variables are defined in Table 1. All regressions apply the Linear Probability Model. All standard errors are double-clustered at the VC-pair level and the company level, and they are reported in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Coinvestment	Coinvestment	Coinvestment	Coinvestment
Past-coinvestments	0.050***	0.046***	0.044***	-0.019***
	(0.003)	(0.003)	(0.003)	(0.004)
Same-company	62.377***	62.369***	62.348***	62.163***
	(1.142)	(1.136)	(1.135)	(1.132)
Round-amount		0.187***	0.188***	0.189***
		(0.009)	(0.009)	(0.009)
Company-age		-0.006***	-0.006***	-0.006***
		(0.002)	(0.002)	(0.002)
Experience-avg		-0.026	0.031	0.253***
		(0.026)	(0.030)	(0.032)
Industry-avg		0.912***	0.998***	0.824***
		(0.078)	(0.085)	(0.080)
State-avg		0.848***	1.051***	0.987***
		(0.063)	(0.075)	(0.072)
Stage-avg		0.375***	0.427***	0.411***
		(0.087)	(0.089)	(0.089)
Deal FE	No	Yes	Yes	Yes
VC FE	No	No	Yes	No
VC-Pair FE	No	No	No	Yes
Observations	1,420,945	1,420,945	1,420,945	1,420,945
R-squared	0.348	0.350	0.350	0.352

Table 5: Exit performance

This sample includes 9,390 VC-pair-company-round observations between 1990 and 2012. Each observation represents a realized coinvestment made by a pair of VCs for which the performance measures are available. The dependent variable in Column (1) is IPO, a dummy variable to indicate whether the company has an IPO. The dependent variable in Column (2) is Exit, a dummy variable to indicate whether the company has an IPO or gets acquired by another company. The rest of the variables are defined in Table 1. All regressions apply the Linear Probability Model. All standard errors are double-clustered at the VC-pair level and the company level, and they are reported in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) IPO	(2) Exit
Past-coinvestments	-0.351**	-0.319*
	(0.148)	(0.181)
Same-company	0.004	-0.403
	(1.375)	(1.450)
Round-amount	7.316***	3.243***
	(0.940)	(0.991)
Company-age	-0.138	0.254
	(0.398)	(0.439)
Experience-avg	1.062	0.041
	(3.963)	(4.574)
Industry-avg	2.695	7.034
	(11.499)	(12.490)
State-avg	-4.927	18.662*
	(9.363)	(10.309)
Stage-avg	-34.991***	-18.768*
	(9.001)	(9.992)
Deal FE	Yes	Yes
VC Pair FE	Yes	Yes
Observations	9,390	9,390
R-squared	0.422	0.360

Table 6: Exit performance using Heckman model

The sample includes 1,420,945 VC-pair-company-round observations between 1990 and 2012. We apply the Heckman two-step model. In the first stage, the dependent variable is Coinvestment, a dummy variable to indicate whether the VC-pair coinvests in the current company round. In the second stage based on all realized coinvested rounds, the dependent variable is either IPO or Exit to proxy for investment performance. IPO is a dummy variable to indicate whether or not the company has an IPO while Exit is a dummy variable to indicate whether or not the company has an IPO or gets acquired by another company. The first stage results are given in Column (1) and the second stage results are reported in Columns (2) and (3). The rest of the variables are defined in Table 1. All standard errors are reported in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	(1) Coinvestment Heckman 1st	(2) IPO Heckman 2nd	(3) Exit Heckman 2nd
Common-markets	0.020***		
	(0.003)		
Indirect- partners	-0.018***		
	(0.006)		
Past-coinvestments	-0.012***	-0.372***	-0.304***
	(0.001)	(0.103)	(0.116)
Same-company	3.065***	9.372	8.352
	(0.017)	(11.988)	(13.469)
Round-amount	0.220***	7.842***	4.070***
	(0.006)	(0.865)	(0.972)
Company-age	-0.026***	0.020	0.273
	(0.002)	(0.176)	(0.198)
Experience-avg	0.132***	1.307	0.339
	(0.027)	(2.362)	(2.654)
Industry-avg	0.876***	2.628	8.311
	(0.061)	(6.337)	(7.120)
State-avg	0.233***	4.414**	9.512***
	(0.023)	(2.112)	(2.372)
Stage-avg	0.185***	-32.674***	-19.161***
	(0.069)	(5.774)	(6.487)
Deal-FE	Yes	Yes	Yes
VC Pair FE	Yes	Yes	Yes
Observations	1,030,642	1,030,642	1,030,642

Table 7: Younger versus older relationships

The sample includes 1,420,945 VC-pair-company-round observations between 1990 and 2012. The dependent variable in Column (1) is Coinvestment, a dummy variable to indicate whether the VC-pair coinvests in the current round. The dependent variable in Column (2) is IPO, a dummy variable to indicate whether or not the company has an IPO. The dependent variable in Column (3) is EXIT, a dummy variable to indicate whether or not the company has an IPO or gets acquired by another company. The rest of the variables are defined in Table 1. All regressions apply the Linear Probability Model. All standard errors are double-clustered at the VC-pair level and the company level, and they are reported in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Dependent variable:	Coinvestment	IPO	EXIT
Younger-coinvestments	0.028***	-0.700***	-0.523*
	(0.009)	(0.246)	(0.276)
Older-coinvestments	-0.050***	-0.135	-0.192
	(0.006)	(0.200)	(0.256)
Same-company	62.160***	0.008	-0.401
	(1.132)	(1.376)	(1.450)
Round-amount	0.189***	7.327***	3.250***
	(0.009)	(0.937)	(0.988)
Company-age	-0.006***	-0.152	0.245
	(0.002)	(0.394)	(0.444)
Experience-avg	0.242***	1.078	0.050
	(0.032)	(3.970)	(4.582)
Industry-avg	0.821***	2.818	7.106
	(0.080)	(11.479)	(12.488)
State-avg	0.981***	-4.889	18.684*
	(0.071)	(9.365)	(10.308)
Stage-avg	0.414***	-34.950***	-18.744*
	(0.089)	(8.994)	(9.992)
Deal-FE	Yes	Yes	Yes
VC-Pair FE	Yes	Yes	Yes
Observations	1,420,945	9,390	9,390
R-squared	0.352	0.422	0.360

Table 8: Relationships in hot versus cold markets

The sample includes 1,420,945 VC-pair-company-round observations between 1990 and 2012. In Panel A, the dependent variable is Coinvestment, a dummy variable to indicate whether the VC-pair coinvests in the current round. In Panel B, the dependent variables are IPO in Column (1) and EXIT in Column (2) to proxy for investment performance. IPO is a dummy variable to indicate whether or not the company has an IPO while Exit is a dummy variable to indicate whether or not the company has an IPO or gets acquired by another company. The rest of the variables are defined in Table 1. All regressions apply the Linear Probability Model. All standard errors are double-clustered at the VC-pair level and the company level, and they are reported in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Coinvestment

	(1)	(2)	(3)
Dependent variable:	Coinvestment	Coinvestment	Coinvestment
Past-hot-coinvestments	-0.048***		
	(0.006)		
Past-cold-coinvestments	0.022***		
	(0.006)		
Past-coinvestments x Now-hot		-0.023***	
		(0.005)	
Past-coinvestments x Now-cold		-0.010	
		(0.007)	
Past-hot-coinvestments x Now-hot			-0.043***
			(0.006)
Past-hot-coinvestments x Now-cold			-0.065***
			(0.011)
Past-cold-coinvestments x Now-hot			0.009
			(0.009)
Past-cold-coinvestments x Now-cold			0.032***
			(0.008)
Now-hot	-0.039	-0.009	
	(0.027)	(0.029)	
Round-amount	0.191***	0.190***	0.190***
	(0.009)	(0.010)	(0.009)
Company-age	-0.007***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)
Other controls	Yes	Yes	Yes
Deal-FE	Yes	Yes	Yes
VC-Pair FE	Yes	Yes	Yes
Observations	1,420,945	1,420,945	1,420,945
R-squared	0.352	0.352	0.352

Panel B: Exit performance

	(1)	(2)
Dependent variable:	IPO	EXIT
Past-hot-coinvestments x Now-hot	-0.429**	-0.207
	(0.182)	(0.216)
Past-hot-coinvestments x Now-cold	-0.669**	-0.860**
	(0.295)	(0.395)
Past-cold-coinvestments x Now-hot	-0.069	-0.546
	(0.357)	(0.356)
Past-cold-coinvestments x Now-cold	-0.232	-0.217
	(0.285)	(0.356)
Now-hot	-0.069	-0.444
	(1.376)	(1.449)
Round-amount	7.298***	3.188***
	(0.934)	(0.945)
Company-age	-0.139	0.252
	(0.398)	(0.437)
Other controls	Yes	Yes
Deal-FE	Yes	Yes
VC-Pair FE	Yes	Yes
Observations	9,390	9,390
R-squared	0.422	0.361

Table 9: Network centrality

The sample includes 1,420,945 VC-pair-company-round observations between 1990 and 2012. In Panel A, the dependent variable is Coinvestment, a dummy variable to indicate whether the VC-pair coinvests in the current round. In Panel B, the dependent variables are IPO in Column (1) and EXIT in Column (2) to proxy for investment performance. IPO is a dummy variable to indicate whether or not the company has an IPO while Exit is a dummy variable to indicate whether or not the company has an IPO or gets acquired by another company. The rest of the variables are defined in Table 1. All regressions apply the Linear Probability Model. All standard errors are double-clustered at the VC-pair level and the company level, and they are reported in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Coinvestments

	(1)	(2)	(3)
Dependent variable:	Coinvestment	Coinvestment	Coinvestment
Degree-avg	0.057*	0.091***	0.013
	(0.029)	(0.030)	(0.029)
Past-coinvestments		-0.096***	-0.166***
		(0.020)	(0.022)
Degree-avg x Past-coinvestments			0.073***
			(0.011)
Round-amount	0.189***	0.189***	0.190***
	(0.009)	(0.009)	(0.009)
Company-age	-0.006***	-0.007***	-0.006***
	(0.002)	(0.002)	(0.002)
Other controls	Yes	Yes	Yes
Deal-FE	Yes	Yes	Yes
VC-Pair FE	Yes	Yes	Yes
Observations	1,420,945	1,420,945	1,420,945
R-squared	0.352	0.352	0.352

Panel B: Exit performance

Dependent variable:	(1) IPO	(2) IPO	(3) EXIT	(4) EXIT
Degree-avg	4.321*	3.823	4.698*	4.911*
	(2.483)	(2.585)	(2.827)	(2.920)
Past-coinvestments	-1.818***	-1.986***	-1.692**	-1.619*
	(0.698)	(0.768)	(0.810)	(0.876)
Degree-avg x Past-coinvestments		0.221		-0.095
		(0.350)		(0.385)
Round-amount	7.344***	7.348***	3.274***	3.272***
	(0.930)	(0.933)	(0.964)	(0.964)
Company-age	-0.160	-0.158	0.230	0.230
	(0.398)	(0.399)	(0.436)	(0.436)
Other controls	Yes	Yes	Yes	Yes
Deal-FE	Yes	Yes	Yes	Yes
VC-Pair FE	Yes	Yes	Yes	Yes
Observations	9,390	9,390	9,390	9,390
R-squared	0.423	0.423	0.361	0.361