The Dynamics of Venture Capital Syndicates: The Effect of Prior Collaboration among VCs on Value Addition to Entrepreneurial Firms

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Abstract

We analyze the effect of the composition of venture capital (VC) syndicates on value creation to the entrepreneurial firms they invest in. We hypothesize that VCs may learn about each other's skills at value creation when they co-invest together in entrepreneurial firms, allowing for more efficient value creation when they co-invest in subsequent syndicates. Further, if VCs view syndication as a repeated game, this may generate incentives to co-operate to a greater extent with each other when investing together in a syndicate, reducing the probability of conflicts among VCs. We empirically analyze the implications of these hypotheses and find the following. First, prior collaboration between a lead VC and any of the VCs in a syndicate leads to greater short-term value creation, as evidenced by greater sales growth, employment growth, probability of patented innovation, and the quality of innovations generated during the three years subsequent to VC syndicate investment. Second, prior collaboration between the lead VC and at least one of the syndicate members leads to greater long-term value creation, as evidenced by the higher probability of a successful exit (IPO or acquisition). Third, if the prior collaboration is very successful (leading to an IPO exit resulting from the previous collaboration), then there is even greater value creation by the VC syndicate compared to the case where the prior collaboration was less successful. Finally, consistent with prior collaboration allowing VCs to learn about each other's value creation skills and reducing potential conflicts among the VCs forming a syndicate, syndicates with prior collaboration between the lead VC and at least one syndicate member are characterized by more uniform syndicate compositions across financing rounds.

Keywords: Venture Capital Syndicates; Syndicate Composition; Entrepreneurial Firms; Value Addition; Prior Collaboration; IPOs

1 Introduction

It is now well known that venture capitalists (VCs) add considerable value to entrepreneurial firms through a variety of channels (see, e.g.,Chemmanur et al. (2011) or Chemmanur et al. (2014)) and further, often invest in entrepreneurial firms as part of teams called "syndicates." There has also been considerable research on the rationale for VC syndication, both theoretically (see, e.g., Casamatta and Haritchabalet (2007)) and empirically (see, e.g., Brander et al. (2002)). However, there is relatively less research on how venture capitalists choose other VCs to form syndicates with and on the composition of VC syndicates that are conducive to adding value to entrepreneurial firms most efficiently. In this paper, we hypothesize that the ability of VC syndicates to add value to entrepreneurial firms is the greatest when at least some members of the VC syndicate have co-invested together previously and even greater when the prior co-investment has been particularly successful (i.e., led to a very successful exit such as an IPO rather than to a less successful exit such as an acquisition or an unsuccessful exit). This is because each VC may face some information asymmetry about the ability of other VCs to add value to entrepreneurial firms as part of a VC syndicate and about the complementarity of the VC's skills with those of another VC (it is reasonable to expect each VC to have some private information about its own value addition skills and deficiencies). In this paper, we argue that, when two VCs co-invest together, this may allow them to learn about each others' value-addition skills and about the complementarity (if any) between each others' value-addition skills. Further, if each VC views the syndication process as a repeated game, this would increase its incentive to co-operate with other VCs forming part of the syndicate for any given entrepreneurial firm: i.e., the repeated nature of the syndication process may reduce the potential for conflicts among VCs forming the syndicate financing a given entrepreneurial firm.

The above arguments generate a number of research questions that we examine empirically in this paper for the first time in the literature. First, does prior collaboration between an entrepreneurial firm's lead VC and some syndicate members result in greater short-run value addition to the firm compared to a situation where there has been no such prior collaboration? We use the sales growth and employment growth of an entrepreneurial firm in the three years immediately after VC investment and the probability of a patented innovation being generated by an entrepreneurial firm and the quality of innovations generated in the three years subsequent to VC investment as measures of short-run value addition. Second, does prior collaboration between an entrepreneurial firm's lead VC and some syndicate members result in greater long-run value addition to the firm compared to a situation where there has been no such prior collaboration? As is standard in the literature, we make use of the probability of a successful exit (an IPOs or an acquisition) by the entrepreneurial firm as the measure of long-run value addition by a VC syndicate. Third, do VC syndicates where the lead VC and some syndicate members have collaborated very successfully (i.e., led to an IPO exit) in the past result in greater short-run and long-run value addition compared to value addition by those syndicates where there has been prior collaboration between the lead VC and some syndicate members but the collaboration has not been as successful? We are motivated to ask this question, since prior collaborative success suggests greater complementarity between the skills of the VCs involved and therefore their ability to add greater value in future syndicates for entrepreneurial firms.

Fourth, if indeed prior collaboration reduces information asymmetry among VCs about each other's value addition skills and reduces the potential for conflicts among syndicate members, one would expect VCs characterized by prior collaboration among syndicate members to be characterized by greater uniformity in the composition of their VC syndicates across financing rounds (when investing in a given entrepreneurial firm). This is because, in such syndicates characterized by lower information asymmetry across VCs and a smaller potential for conflict among them, there would be less of a need to replace VCs (and potentially bring in new VCs to join the syndicate) across financing rounds. This is therefore the next research question that we address here. Fifth, if VCs are aware that syndicates with other VCs with whom they have collaborated previously indeed leads to greater value addition, then we would expect such VCs to syndicate more often with prior collaborators. Further, if prior collaboration that resulted in greater success leads to even greater value addition than prior collaboration alone, then we would expect VCs to form syndicates with such successful prior collaborators with a greater frequency than syndicates with VCs where the previous collaboration was not as successful. This is the last research question that we address here.

To answer the above research questions, we utilize multiple data sources to compile data on private firms used in our study. The main source from which we collect information about the sample of VC-backed startups is VentureXpert via Thomson One, which is a leading data provider on venture capital investments, funded companies, investing firms, and funds. From VentureXpert we collect round-by-round VC financing information. By collecting such information, we are able to see the identity of the VC investors participating in different rounds of financing for different startup companies. We can thus determine if any pairs of VC investors have co-invested in the past before they invest together in the current focal startup. In this paper, we mainly focus on three sets of outcome variables, which are exit, employment and sales growth, and innovation of startup companies. First, we collect data on startups' exit choices (i.e., IPO or M&A) from Thomson Reuters SDC Platinum New Issues and M&A Database. Second, we collect information on the level of startups' employment and sales from the National Establishment Time Series (NETS) database, based on which we calculate startups' employment and sales growth over the 3 years following their first VC financing. Third, the source from which we collect data on startups' innovation output is USPTO PatentsView database.

Our baseline results can be summarized as follows. First, in terms of the successful exit, we find that startups backed by VC investors who have co-invested in the past are more likely to experience successful exits, as measured by IPOs or M&As. In addition, we also examine the effect of VC investors' past collaboration on the probability of startups going public, since existing literature has argued that from both startups' and VCs' perspectives, going public is a stronger measure of successful exit than being acquired by another company. For startups that choose to exit via IPOs, it indicates that they, as stand-alone firms, are more likely to have a strong edge in the product market and can fend for themselves (Bayar and Chemmanur (2011)). From VCs' point of view, going public could also be a more desirable exit choice compared to the acquisition of their portfolio companies by others, as Sahlman (1990a) finds that VC investors earn the majority of their financial returns from portfolio companies that eventually go public. We find that startups backed by VC investors who have collaborated in the past are also more likely to experience more successful exits, as measured by IPOs alone. The effect of VC investors' past collaboration on the probability of startups' successful exits (as measured by IPO or M&A) is both statistically and economically significant: startups backed by VCs who share prior co-investment experience are 4.45% more likely to exit successfully than those backed by VCs with no prior co-investment experience, or about 10% of the unconditional sample mean.

Second, regarding the employment and sales growth, we document that startups backed by VC investors who have co-invested in the past have higher employment and sales growth over the 3 years after receiving their first VC investment. We find that the effect of VCs' past collaboration on startups' 3-year growth in employment and sales is both statistically and economically significant as well: startups backed by VCs who have co-invested previously are associated with an 8.66% higher employment growth and a 13.17% higher sales growth than those backed by VCs who do not have prior collaboration. The magnitude of these coefficients is equivalent to 6.2% and 7.8% of the unconditional sample mean, respectively.

Third, in terms of startups' innovation output, we find that startups backed by VC investors who have co-invested previously are more likely to obtain at least one patent (that is eventually granted) during the 3 years subsequent to their first VC financing. Further, these startups also generate patents of higher quality (as measured by the number of citations per patent of a firm) during the same period compared to their counterparts. We show that startups backed by VCs who share prior co-investment experience are 4% more likely to obtain at least one new patent and are associated with a 4% larger number of citations per patent for patents filed (and eventually granted) within the 3 years after the first VC investment. This translates to 20% and 28% of their unconditional sample mean, respectively.

Our baseline results suggest that there is a positive relationship between VC investors' past collaboration and the future success of startups backed by them, as measured by startups' successful exits, employment and sales growth, and innovation output. However, there are several endogeneity concerns facing our baseline specifications. One such concern is the selection versus treatment effect of VC investors frequently studied in the entrepreneurial financing literature. Specifically, is the outperformance of startups backed by VCs with past collaboration experience due to these VC investors' ability to select better firms (i.e., selection/screening effect)? Or is it because these VCs have the ability to better create value for startups backed by them (i.e., treatment effect)? To disentangle the selection effect from the treatment effect, we conduct an Instrumental Variable (IV) analysis.

In this paper, we construct our IV as the number of pairs between the lead VC of a startup and any other syndicate members from the first round of financing that has a distance less than 50 miles between the MSAs of their headquarters.[1] Then we use this IV to instrument for the endogenous variable of the past collaboration between the lead VC and any other syndicate members from the first round of the startup. We argue that our IV is likely to satisfy the relevance condition and exclusion restriction. In terms of the relevance of our IV, we argue that VC investors are more likely to co-invest with each other when they are located closer, since it is more likely for VCs located closer to each other to share investment opportunities and develop investment networks. We also empirically show in the first stage of the IV analysis that our IV is relevant. In terms of the exclusion restriction, we argue that the geographic proximity between lead VC and syndicate members of a startup is likely to affect the startup's performance only through the likelihood of VC investors sharing past collaboration experience rather than through the underlying startups' characteristics. Therefore, by utilizing the IV to instrument for the endogenous variable of past collaboration, we are able to disentangle the selection effect from the treatment effect and to examine if VCs having prior co-investment experience indeed create value for the startup that they currently invest in. The results from our IV analysis show that VCs that have collaborated in the past indeed add value to startups backed by them. We show that the past collaboration of VCs causally leads to startups having greater chances of successful exits, enjoying larger employment and sales growth, having a higher probability of filing for new patents, and achieving higher innovation quality.

Next, we discuss several potential mechanisms that could drive our results. The first potential mechanism through which VCs' past collaboration creates value for startups is the reduction in information asymmetry and potential conflicts between VCs. If two VC investors have collaborated with each other and co-invested in some startups together before, they are more likely to know each other very well (i.e., the extent of information asymmetry is lower), and the potential conflicts between them is likely to be lower. As a result, they are more likely to form a more stable/uniform syndicate for the startup that they currently invest in. If the VC syndicate is more stable across different financing rounds of a startup, the startup is likely to face less financing uncertainty and hence could achieve higher growth in the long term. We find that the past collaboration between the lead VC and any other syndicate members of a startup positively and significantly predicts the stability of VC syndicate across different financing rounds of the startup, which lends support to

[1] In Section 5.5, we also construct several alternative IVs using different distance cutoff points. The results are robust to different distance cutoff points

this potential mechanism.

The second potential mechanism we conjecture is the complementary skills and coordination efficiency between VCs. We test this mechanism by examining the past success achieved by VC pairs. In this paper, we define that a VC pair achieves past success if they have successfully brought a previous startup they co-invested into IPO, since we mentioned above that IPO is probably a more successful exit than M&A from both a startup's and its VC investors' points of view.[2] We conjecture that if a VC pair was able to help a previous startup that they co-invested in to go public, it could be the case that the VC pair has some complementary capabilities and can co-ordinate efficiently, such that together they could create greater value for future startups than others can. It is also possible that from this past success experience has the VC pair learned valuable know-how, which they could lever into the current startup they are co-investing in. In any circumstance, if past success is indeed one of the channels driving our results, we would expect to find that the future success of startups (as measured by the successful exit, employment and sales growth, as well as innovation output) is more pronounced in the sub-sample where their VC investors share some previous successful experience. We find that this is indeed the case. We show that conditional on the sub-sample of startups whose VC investors from the first round have collaborated in the past, past success of their VC investors positively and significantly predicts the probability of startups' successful exits, the 3-year employment and sales growth of startups, the probability of startups applying for new patents over the 3 years following the first VC investment, and startups' innovation quality during the 3 years subsequent to their first VC financing.

The rest of this paper is organized as follows. Section 2 discusses the existing literature related to our paper and our contribution to the literature. Section 3 develops several testable hypotheses for our empirical analysis. Section 4 discusses the data sources used in our study and the sample selection procedure. Section 5 presents our main empirical tests and results on the effect of past VC collaboration on value addition by VC syndicates. Section 6 examines several potential mechanisms through which the past collaboration among VCs in a syndicate allows them to create greater value for entrepreneurial firms. Section 7 concludes.

[2]In an untabulated analysis, we also define the past success of a VC pair as a startup backed by them going public or being acquired by another firm. The results remain quite consistent with what we document in this paper.

2 Related literature

Our paper contributes to two strands in the existing literature. The first strand is the broad literature analyzing the value-adding role of VC investors in their portfolio companies. The theoretical literature includes papers on the optimal contracting and the advising role of VC (e.g., Sahlman (1990b), Berglöf (1994), Admati and Pfleiderer (1994), Hellmann (1998), and Ueda (2004), Casamatta (2003), Schmidt (2003)). The empirical literature includes papers on the monitoring and value-adding role of VC (e.g., Lerner (1995), Kaplan and Strömberg (2004), Hellmann and Puri (2002), Bernstein, Giroud, and Townsend (2016), Chemmanur, Krishnan, and Nandy (2011), Chemmanur, Loutskina, and Tian (2014), González-Uribe (2020)).[3] We extend the above literature by studying the role of past collaboration between VCs in improving the post-investment performance of startups.

The second strand is the theoretical and empirical literature on VC syndication formation. Casamatta and Haritchabalet (2007) theoretically argue that the rationale for the lead VC to form syndication is to gather information while preventing competition from syndicate members. Cestone, White, and Lerner (2007) also theoretically analyze how an optimally designed contract of cash flow rights among VC syndicate members helps induce truthful information revelation (see also Bachmann and Schindele (2006)). Brander, Amit, and Antweiler (2002) show theoretically and empirically that VC syndication helps improve more on VC's post-investment treatment effects than VC's pre-investment screening abilities. Unlike the above papers, Admati and Pfleiderer (1994) focus on optimal contracting in sequential syndication within the same startup for lead VCs to resolve informational asymmetries between outside investors (i.e., syndicate members in the future rounds) and startups. In a similar vein, Bayar, Chemmanur, and Tian (2020) theoretically and empirically show that firms financed by a stable set of VCs across various financing rounds are more likely to have a successful exit outcome. However, unlike Admati and Pfleiderer (1994) and Bayar, Chemmanur, and Tian (2020), we focus on the collaboration experience between VCs across deals invested in different companies. Other papers have examined which characters drive the outcomes of the syndication. Hochberg et al. (2007) analyze the role of networks and show that the portfolio companies of better-networked VCs are more likely to have successful exits such as IPO

[3] See Da Rin, Hellmann, and Puri (2013) for a detailed literature review on venture capital financing.

or acquisitions. Bottazzi et al. (2016) theoretically and empirically examine the effect of trust in cross-country VC investment and suggest that syndication is more valuable in low-trust deals. More recently, Bubna, Das, and Prabhala (2020) show that VCs with similar ages and functional styles are more likely to form syndication and subsequently have a better effect on startups in terms of better exit outcomes and greater innovation.[4]. Overall, our paper contributes to this literature by analyzing the dynamics of VC syndicates in investment deals across different startups for the first time in the literature.[5]

3 Theory and Hypothesis Development

We posit that there may be two advantages if venture capitalists constituting a syndicate may have had a prior collaboration (in terms of serving together previously in a VC syndicate investing in an entrepreneurial firm in the past). First, the VCs may know each others' skills and abilities better; in other words, each VC may have a larger amount of information (i.e., have a lower extent of information asymmetry) about the other VCs in the syndicate. Second, if two VCs believe that they are playing a sequential game in terms of being part of the same VC syndicate , then they have more of an incentive to co-operate with each other in terms of value creation for the entrepreneurial firm they are investing in (in other words, there will be fewer conflicts among VCs serving in the VC syndicate investing in an entrepreneurial firm).

Both of the above effects will lead to greater efficiency in value addition by VCs in a syndicate if some of the VCs in a syndicate have had a prior collaboration in terms of investing together in an entrepreneurial firm in the past compared to a situation where there has been no such previous collaboration. This is the first hypothesis that we test here **(H1)**. We will use the following measures of value creation in our empirical analysis: probability of successful exit; employment growth in the entrepreneurial firms subsequent to VC investment; sales growth in the entrepreneurial firms subsequent to VC investment; probability of having successful innovation output; and finally, the

[4]There are also several papers in the areas of management and strategy that study the prior collaboration between VCs. For example, Bellavitis et al. (2020) document a U-shaped relationship between the number of prior co-investments between VCs and the probability of a startup exiting successfully through an initial public offering or a M&A. In a different paper, Wang et al. (2022) find a slightly different result that as the number of past collaboration among a group of VCs increases, a startup backed by this group of VCs is more likely to exit by a M&A, while a lower number of past collaboration among VCs is associated with a higher probability of a startup exiting by IPOs.

[5]Our paper is also broadly related to the literature on team and alliance formation (see, e.g., Pichler and Wilhelm (2001), Robinson (2008)).

quality of firms' innovation output.

We now turn to an empirical analysis of the mechanisms through which VCs who have collaborated with each others in the previous VC syndicates are able to create greater value for entrepreneurial firms. If, as we have mentioned earlier, prior collaboration allows VCs to learn about each others' ability to add value to entrepreneurial firms, and also allows the minimization of conflicts among the VCs constituting a VC syndicate, we would expect there to be a greater degree of uniformity of syndicate membership across financing rounds (since, when VCs have more information about each other and have fewer conflicts among them, there is less of a need to remove a VC from a syndicate and bring in a new VC instead). This is the second hypothesis that we test here **(H2)**.

Even when VCs have collaborated with each other in the past, there may be considerable variation in the extent of the success of their past collaboration. In some cases, the entrepreneurial firms whose syndicate that two VCs have previously collaborated on may have had an extremely successful exit; namely, an IPO; in other cases, the entrepreneurial firms may have had a less successful exit, namely, an acquisition, or worse, an unsuccessful exit. The success of previous VC collaborations is important since this may indicate the collaborating VCs' ability to complement each other and co-ordinate with each other efficiently without conflicts in creating value for entrepreneurial firms that they invest in.[6] This leads to the testable hypothesis that VC syndicates containing VCs who have very successfully collaborated in the past (i.e., their collaboration resulted in an IPO) are ale to create greater value than VC syndicates where the VCs have collaborated in the past without as much success. This is the next hypothesis we test here **(H3)**.

We now turn to the characteristics of other VCs with whom a VC prefers to form a syndicate. If a VC is aware that forming a syndicate with another VC with whom they have collaborated previously enables greater value addition, then that VC has a greater propensity to form a syndicate with such a VC **(H4)**. Further, if a VC believes that (as we hypothesized above) syndicating with a VC with whom they have had a successful collaboration (i.e., a collaboration which led to an IPO outcome) enables greater value creation, then we would expect to see a higher probability of such a syndicate

[6] Even if two VCs' prior collaboration was not particularly successful, having a past collaboration reduces the information asymmetry across the two VCs involved. Therefore, analyzing whether the prior collaboration was very successful or not allows us to dig deeper into the mechanism through which prior collaboration allows VCs to add value to entrepreneurial firms more efficiently.

formation relative to the probability of forming a syndicate with a VC with whom that VC's prior collaboration was not as successful **(H5)**. These are the last two hypotheses we test here.

4 Data and Sample Selection

4.1 Data Sources

The main source from which we collect information about the VC-backed entrepreneurial firms is VentureXpert via Thomson One. VentureXpert is a leading provider of data on venture capital investments, funded companies, investing firms, and funds, and it is frequently used by previous studies. From VentureXpert we collect round-by-round VC financing information. By collecting such information, we can see the identity of the VC investors participating in different rounds of financing for different startup companies. Hence we are able to determine if any pairs of VC investors have co-invested in the past before they invest together in the current focal startup. Among other variables, in particular, we collect information about the investment amount of individual VC firms in different rounds of a startup company, as well as the geographic locations (specifically, MSAs) of VC firms' headquarters. We collect information about the investment amount to determine the lead VC investor of a startup company. We then use this information to construct, for each startup, pairs between lead VC and any other syndicate members from the first round and examine if any of these pairs have collaborated in the past to invest in a startup company. We collect information about the geographic locations of VC firms' headquarters, which we later use to construct the Instrumental Variable (IV) used in our analysis. We will discuss the IV analysis in detail in Section 5.4.

We focus on three sets of outcome variables of startups in this paper, which are exit, employment and sales growth, and innovation. First, the data source from which we collect startup companies' exit is Thomson Reuters SDC Platinum New Issues and M&A Database. We merge firms in the Thomson Reuters SDC database with VentureXpert startup companies based on matching of their standardized names. Second, we collect the data on startups' employment and sales from the National Establishment Time Series (NETS) database, from which we can then calculate startups' employment and sales growth over the 3 years following their first VC financing. We merge firms in the NETS database with VentureXpert startup companies using fuzzy name match and location. Lastly, we obtain the data on startups' innovation output from USPTO PatentsView. To examine startups' filings of new patents during 3 years following their first VC financing, we first obtain application information of utility patents (that are eventually granted) from "application" dataset of USPTO PatentsView Bulk Download Database. We then use the patent-assignee crosswalk file provided by USPTO to aggregate the above information to the firm level. We use the "application" dataset (instead of the dataset of granted patents) because it is usually in the year of a company filing for a patent that the company has possessed the technology embedded in the patent. To examine startups' innovation quality, following the existing literature in corporate innovation, we use the number of citations per patent constructed at the firm level as a proxy. We obtain the citation information of utility patents from "uspatentcitation" dataset and then aggregate this information to the firm level as well.

As frequently discussed in the innovation literature (e.g., Hall, Jaffe, and Trajtenberg (2001)), there are two types of truncation problems associated with patent data. The first type of truncation problem is related to patent count. A patent filed by a company will appear in the USPTO patent database only after it is granted. Based on the data from USPTO, the time lag between the filing and grant of a patent is 2 years on average. Therefore, toward the end of our sample period, the number of patents filed by a firm in a given year is likely to be reduced compared to earlier years of our sample period, since it will take time for these later patents to be granted before they appear in the USPTO patent application dataset. The second type of truncation problem is associated with the number of citations received by a given patent. Patents filed and granted in earlier years of the sample period are expected to receive a larger number of citations than patents filed in later years. To mitigate these two types of truncation problems, we follow a similar methodology to that in Hall, Jaffe, and Trajtenberg (2001) and Seru (2014). Specifically, we scale a patent (number of citations received by a patent) by the total number of patents (total number of citations received by all the patents) filed in the same year and technology class. We then aggregate these class-adjusted measures to firm level and use them to construct the innovation-related outcome variables used in our analysis.

4.2 Sample Selection

We start by selecting from VentureXpert the startup companies that receive their first VC investment between 1980 and 2019. We focus on startup companies with their headquarters located in the United States. We first drop VC firms with unknown identity (i.e., VC firm names that contain ”undisclosed”), since we need the identity of VC firms to determine if any pairs of VC firms have co-invested together in the past. Further, following Bayar, Chemmanur, and Tian (2020), we drop investing firms with their types being “Angel Group” or “Individuals”, since these firms are not the main focus of our study. This initial screening procedure leads to a sample of 49,970 startup companies.

Building on the previous sample, we focus on startups that have at least two VC investors investing in the first round, since this will allow us to determine if any *pair* of VC investors has collaborated in the past to invest in a startup company. Throughout our analysis, we focus on the pairs between lead VC investor of a startup and any other syndicate members from the first-round financing of the startup. We choose to study the past collaboration of VC pairs in the first round, because first-round financing is often assumed to be important for a startup to kick off its business and continue to grow subsequently. In addition, we focus on the pairs between lead VC investor of a startup and any other syndicate members, since it is argued by the existing literature that the lead VC investor often takes on the job of monitoring and overseeing a startup’s operation and hence plays a bigger role in the startup’s growth. It should be noted that, when we determine if a pair between the lead VC investor of a startup and a syndicate member has co-invested in the past, we use all the previously available round-by-round financing data prior to their investment in the current focal startup. Overall, this leads to a final cross-sectional sample with 19,393 startup companies. We report the summary statistics in Table 1. We winsorize all of the continuous variables at 2.5% and 97.5% level.

5 Empirical Tests and Results

5.1 Past VC Collaboration and Successful Startup Exit

In this subsection, we study whether the past collaboration experience between the lead VC and any of its syndicate members leads to better exit outcomes for the startups after they have invested together in the first round. We use two measures to define a successful exit by a startup. Our first measure is *IPO or M&A*, which is a dummy variable that equals one if a startup exits via IPO or Mergers & Acquisitions (M&A) by the end of our sample period (2019) and zero otherwise. Our second measure is *IPO*, which is a dummy variable that equals one if a startup exits via IPO and zero otherwise. More specifically, we study the relationship between VC past collaboration and startup exits by estimating the following regression:

$$y_{i,t} = \alpha + \beta \textit{Past Collaboration}_{i,t} + \gamma Z_{i,t} + \textit{Industry}_j + \textit{Year}_t + \epsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ represents our measures of startup exit: *IPO or M&A*, and *IPO*. Our key independent variable is *Past Collaboration*, which is also a dummy variable that equals one if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round and zero otherwise. $Z_{i,t}$ represents a set of variables that we use to control for startup, lead VC, and investment deal characteristics, which includes *Startup_Age*, *Emp*, *VC_Age*, and *First_Round_Inv*. *Startup_Age* measures the age of a startup and is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* count the number of employees of a startup at the time when it receives its first VC investment. *VC_Age* measures the age of the lead VC investor in an investment deal and is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in millions) received by a startup in the first round. $\textit{Industry}_j$ and $\textit{Year}_t$ represent the 2-digit SIC industry and year fixed effects included in our regressions. Standard errors are also clustered at the industry and year levels.

The results of our regressions are reported in Table 2. Columns (1) - (3) of Table 2 show that the coefficient estimates of *Past Collaboration* are positive and significant across three different specifications when using *IPO or M&A* as our dependent variable. These results suggest that the past collaboration experience between lead VC and any of its syndicate members is associated with a higher probability of exiting successfully via IPO or M&A by their portfolio companies. Further, Columns (4) - (6) of Table 2 show that the coefficient estimates of *Past Collaboration* remain positive and significant after we switch our dependent variable from *IPO or M&A* to *IPO*. In other words, our main findings still hold even if we use a stricter definition of successful exits by counting IPO exits only. The magnitudes of these coefficients also indicate their economic significance. For example, the past collaboration experience between the lead VC and its syndicate members increases their startup's probability of exiting through IPO by a magnitude of 2.4% (i.e., a 21% increase compared to the average probability of exiting via IPOs). Overall, the above findings show that the past collaboration experience between the lead VC and any of its syndicate members contributes to a significantly higher probability of exiting successfully via IPO or M&A by their portfolio companies.

5.2 Past VC Collaboration, Startup Employment Growth, and Startup Sales Growth

In this subsection, we study whether the past collaboration experience between the lead VC and any of its syndicate members is associated with higher employment and sales growth of the startups after they have invested together in the first round. We use the 3-year employment growth (in percentage terms) of a startup starting from the year when it receives its first VC investment to measure post-investment employment growth ($\Delta\%$*Emp_3y*). Similarly, we use the 3-year sales growth (in percentage terms) of a startup starting from the year when it receives its first VC investment to measure post-investment sales growth ($\Delta\%$*Sales_3y*). To study the relationship between VC past collaboration and startup employment and sales growth, we also estimate Equation 1 by replacing $y_{i,t}$ with our measures of employment and sales growth: $\Delta\%$*Emp_3y* and $\Delta\%$*Sales_3y*.

The results of our regressions are reported in Tables 3 and 4 . Table 3 shows that the coefficient estimates of *Past Collaboration* are positive and significant across three different specifications, suggesting that startups invested by lead VCs who have past collaboration experience with any of their syndicate members have been growing faster in terms of employment in the three years after receiving their first VC investment. Similarly, Table 4 shows that the coefficient estimates of *Past Collaboration* are also positive and significant, suggesting a similar positive effect of that the past collaboration experience between lead VC and any of its syndicate members on the post-investment sales growth of startups. Economically, the past collaboration experience between the lead VC and its syndicate members increases their startup's 3-year employment growth rate by 58% (i.e., a 41% increase compared to the average 3-year employment growth rate) and their startup's 3-year sales growth rate by 104% (i.e., a 61% increase compared to the average 3-year sales growth rate).

5.3 Past VC Collaboration and Startup Innovation Productivity

In this subsection, we study whether the past collaboration experience between the lead VC and any of its syndicate members is associated with higher innovation productivity of the startups after they have invested together in the first round. Our first measure of a startup's innovation productivity is a dummy variable, *New_Pat_1_3*, which equals one if a startup files any new patents (that are eventually granted) over a three-year window after it receives its first VC investment and zero otherwise. We also measure the average quality of any new patents produced by startups with the average number of citations per patent. More specifically, *CPP_1_3* is the average number of citations per patent of a startup produced over a three-year window after it receives its first VC investment. To study the relationship between VC past collaboration and startup innovation productivity, we also estimate Equation 1 by replacing $y_{i,t}$ with our measures of startup innovation productivity: *New_Pat_1_3* and *CPP_1_3*.

The results of our regressions are reported in Tables 5 and 6 . Table 5 shows that the coefficient estimates of *Past Collaboration* are positive and significant across three different specifications, suggesting that startups invested by lead VCs who have past collaboration experience with any of their syndicate members are more likely to produce new patents in the three years after receiving their first VC investment. The results are also economically significant. For example, the past collaboration experience between the lead VC and its syndicate members leads to a 4% higher probability of producing new patents for their startups over a 3-year period after receiving the first-round VC investment (i.e., a 21% increase compared to the average probability of producing any new patents over the same period). Further, Table 6 shows that the coefficient estimates of *Past Collaboration* are also positive and significant, suggesting that the new patents produced by these startups are, on average higher quality. Put together, the baseline results from Section 5.1 to 5.3 support the prediction of our testable hypothesis **H1**.

5.4 Identification

So far, we have shown that VC past collaboration is positively correlated with startup successful exits and performances. However, an OLS regression is unable to distinguish whether the effect is due to selection, i.e., VCs with prior collaboration tend to select high-quality startups to invest in, or treatment, the past collaboration of VCs enables VCs to add value to startups. In this section, we use an instrumental variable (IV) approach to establish the causal link that the past collaboration of VC syndicate members has a positive impact on startups. That is, the positive correlation we have shown in the baseline regressions is not only due to the joint selection of VCs but also the value addition from VCs that have collaborated in the past.

We construct an IV for the past collaboration of VC syndicate members by counting the number of pairs between lead VC and other syndicate members in the first round that have a distance of less than 50 miles between the MSAs of the VC headquarters. We then use the IV and conduct a two-stage-least-square (2SLS) estimation. The first stage of the estimation is based on the following equations:

$$\textit{Past Collaboration}_{i,t} = \alpha + \beta \textit{Dist\_Less\_50} + \gamma Z_{i,t} + \textit{Industry}_j + \textit{Year}_t + \epsilon_{i,t}, \tag{2}$$

and the second stage of the estimation as:

$$y_{i,t} = \alpha + \beta Past\hat{Collaboration}_{i,t} + \gamma Z_{i,t} + \textit{Industry}_j + \textit{Year}_t + \epsilon_{i,t}, \tag{3}$$

where i represents a startup, t is the year that the startup receives the first round of financing. Other variables are defined the same as in our baseline regressions.

Geographical distance between VCs is likely to satisfy the identification assumptions for the IV approach. Regarding the correlation assumption, VCs are more likely to collaborate with each other when they are close. Figure 1 shows that about 35% of the pairs between lead VC and other syndicate members have a distance less than 100 miles. As shown later in this section, the first-stage estimations all have a F-stat greater than 10, passing the critical value required by Stock and Yogo (2005). In terms of the exclusion restriction of the IV approach, we argue that the geographical distance between VCs is likely to affect startup performances only through the likelihood of having a past collaboration.

First, we show the results of our IV analysis of the impact of VC past collaboration on the successful exits of entrepreneurial firms. Table 7 shows the result. In the first stage of the analysis, we instrument the past collaboration variable in the first round of financing (*Past Collaboration*) using the the geographical distance between lead VCs and other syndicate members (*Dist_Less_50*). In the second stage of the analysis, we regress the variables that represent successful exits on the predicted value of *Past Collaboration* from the first stage. Columns (1) and (3) shows the first-stage results. Consistent with our earlier discussion about the IV, we find that a positive correlation between the number of geographically close pairs between the lead VC and the syndicate members and their past collaboration. The Kleibergen-Paap rk Wald statistic (Kleibergen and Paap, 2006), which tests directly whether the IV predicts a sufficient amount of the variation in the endogenous variables to identify our equations, has a value of 159.16 and is far beyond the critical value required by Stock and Yogo (2005) for the IV estimates to have no more than 10% of the bias of the OLS estimates. Therefore, we empirically show that our IV is relevant. Columns (2) and (4) report the second-stage results of the IV analysis, where the dependent variables are the dummy variables for having an successful exit such as IPO or M&A (*IPO or M&A* and *IPO*). The coefficient estimates are both positive and statistically significant at the 5% significance level, suggesting a causal impact of having past collaboration on the successful exits of startups.

We then perform the IV analysis and examine the relationship between VCs' past collaboration and the employment growth and sales growth of startups. Table 8 presents the results when the dependent variable of the second-stage regression is the 3-year employment growth of a startup. The first-stage coefficient estimate on the IV, *Dist_Less_50* is positive and statistically significant at a 5% significance level. The F-stat of the first-stage regression is 61.52, suggesting the first-stage regressions passes the critical value required by Stock and Yogo (2005). Column (2) of Table 8 shows a positive and significant coefficient estimate on the predicted *Past Collaboration*. Table 9 repeats the analysis and we substitute the dependent variable with the 3-year sales growth of a startup. Again, we find a strong first-stage result and a positive coefficient estimate on *Past Collaboration* that is statistically significant at 1% significance level. The above two tables suggests that the positive relationship between VCs' past collaboration and Startups' employment and sales growths is not merely due to better VCs are more likely to investment in higher quality startups but also there are causal impact of VCs' past collaboration on startups' performances.

Finally, we examine the relationship between VCs' past collaboration and innovation outcome of startups using the IV approach. Table 10 presents the results when the dependent variable of the second-stage regression is the dummy variable indicating whether a startup files any new patents that are eventually granted within three years of receiving the first round of financing. Table 10 Column (2) shows a positive and significant coefficient estimate on the predicted *Past Collaboration*, suggesting that VCs' past collaboration has a positive impact on startups' innovation outcome. Table 11 shows the results of the analysis when we use the number of citation per patent for a startup within three years of receiving its first round of financing. Table 11 Column (2) again shows a positive coefficient estimate on *Past Collaboration* that is statistically significant at 1% significance level. The above two tables suggest that VCs' past collaboration has a positive and significant impact on startups' innovation outcome and the quality of patents.

5.5 Robustness Tests

We perform a battery of tests to check the robustness of our main findings. First, we replace our main dummy independent variable, *Past Collaboration*, with a continuous measure of VCs' past collaboration, *Num of Collaboration*. This continuous measure is costructed as the natural logarithm of 1 plus the average number of past collaboration (i.e., number of previous co-investments) between the lead VC investor of a startup and any other syndicate members from the first round. We then repeat our baseline specifications and report the corresponding results in Tables A.1, A.2, and A.3. We find that overall the empirical patterns documented in these tables are very similar to those documented in our baseline results, except that the coefficient on *Num of Collaboration* is not significant at 10% level (but still positive and very close to 10% significance level) when the dependent variable is entrepreneurial firms' 3-year employment growth subsequent to VC investment.

Second, we exclude startups located in three cities, San Francisco, New York, and Boston, with strong VC presences (Chen et al., 2010) and repeat our analyses in Sections 5.1, 5.2, and 5.3. Tables A.4, A.5, and A.6 report the regression results regarding the successful exit, employment and sales growth, and innovation, respectively. All coefficients of our key variable (i.e., *Past Collaboration*) remain largely unchanged both in terms of magnitudes and statistical significance, indicating that our main findings are not mainly driven by startups in the above three cities.

Third, we use different cutoffs of geographical distance (i.e., 25 miles, 100 miles, 150 miles, and 200 miles) to define the geographical proximity between a lead VC and a syndicate member. For example, *Dist_Less_25* is the number of pairs between the lead VC of a startup and any other syndicate members from the first round that has a distance of less than 25 miles between the MSAs of their headquarters. We repeat our IV analyses in Sections 5.4 using these alternative instrumental variables and report the IV results in Tables A1-A5. More specifically, Panel A of each table reports the first-stage regression results with these alternative instrumental variables, whereas Panel B of each table reports the second-stage regression results. We continue to find that the past collaboration experience between the lead VC and any other syndicate members affects startup performance positively and significantly. More importantly, both the magnitude and statistical significance of the coefficient estimate for *Past Collaboration*) are quite stable across different IVs, indicating that our results are not sensitive to the choice of distance cutoffs. Overall, our main findings in both the baseline analyses and the IV analyses are robust to these alternative specifications.

6 Potential Channels for More Efficient Value Creation

6.1 Reduction in Information Asymmetry and Potential Conflicts Between VCs

After establishing that the past collaboration experience between VC pairs indeed creates value for startup companies in terms of successful exit, higher employment and sales growth, and higher innovation capacity, we now explore through which channels the past collaboration experience between VC pairs drives the above effects.

The first potential channel we examine is the reduction in information asymmetry and potential conflicts between VCs. If two VC investors have collaborated with each other and co-invested in some startups before, they are more likely to know each other very well (hence the degree of information asymmetry between them is presumably lower), and the potential conflicts between them is likely to be lower. As a result, they are more likely to form a more stable/uniform syndicate for the startup that they currently invest in. If the VC syndicate is more stable across different financing rounds of a startup, the startup is likely to face less financing uncertainty and hence could achieve a higher growth in the long term. Therefore, we hypothesize that a startup backed by VC investors who have collaborated in the past is more likely to have a stable VC syndicate across different financing rounds.

We follow Bayar, Chemmanur, and Tian (2020) and construct a proxy for the stability of VC syndicate across different financing rounds of a startup. We construct the *VC_Comp* as follows:

$$VC\_Comp = (\sum_{i=1}^{N}\sum_{r=1}^{R} VC_{i,r})/(Num\_VC \times Num\_Rounds) \tag{4}$$

$VC_{i,r}$ in the numerator denotes VC i investing in round r. To construct the numerator, we count the number of rounds in which each VC investor participates, and we then aggregate this across all the VC investors in different rounds. Num_VC in the denominator is the number of VC investors of a startup across all rounds of financing, while Num_Rounds represents the number of rounds of financing a startup receives.[7] The VC_Comp measures the degree of overlap of VC syndicate members of a startup company across all financing rounds. Hence, higher this measure, more stable/uniform a VC syndicate across different financing rounds of a startup company.

To empirically test this channel, we run the following specification. We include the same set of control variables and fixed effects as in Eq. 1. The main right-hand side variable of interest is *Past Collaboration*$_{i,t}$. If the stability of VC composition is one of the channels through which the past collaboration between VCs creates value for startups, we would expect to find β to be positive and significant.

$$\textit{VC\_Comp}_{i,t} = \alpha + \beta \textit{Past Collaboration}_{i,t} + \gamma Z_{i,t} + \textit{Industry}_j + \textit{Year}_t + \epsilon_{i,t}, \tag{5}$$

Table 12 reports the results associated with Eq. 5. In Column (1) of Table 12 where we run a univariate regression of VC composition's stability on the *Past Collaboration* dummy, we document a positive coefficient, which is also statistically significant at 5% level. This suggests that, for a

[7]When constructing this measure, we drop two types of startup companies. The first type of startup companies only has one round of financing. We drop this type because these firms will have $VC\_Comp = 1$. However we cannot tell if the VC composition is stable or not across rounds. The second type of startup companies we drop has multiple rounds of financing, but there is only one VC investor in each round. In this case, the VC_Comp will be equal to $\frac{1}{R}$, where R denotes the total number of financing rounds. If startup A has two rounds of financing and a single (yet different) VC investor in each round, while startup B has five rounds of financing and a single investor in each round, this measure will be 1/2 for A and 1/5 for B. There is no overlap of syndicate members across different rounds for both startups. Yet, the measure for these two companies is different.

startup that is backed by VC investors who have collectively invested in the past, the VC syndicate of this startup is more stable across different financing rounds. When we include industry and year fixed effects in Column (2) and all the company, VC-firm, and deal control variables in Column (3), the results remain, which is consistent with our hypothesis. In other words, these results together indicate that the past collaboration experience between VC pairs affects the future success of startups through the channel of VC composition's stability. This is consistent with the prediction of our testable hypothesis **H2**.

6.2 Complementary Skills and Coordination Efficiency

In this subsection, we explore another potential channel through which the past collaboration experience between VC pairs creates value for portfolio companies, which is the complementary skills and coordination efficiency between VCs. We use the past success experience between VC pairs as a proxy for them. We define that a VC pair achieves past success if they have successfully brought a previous startup they co-invested into IPO. We use IPO as the proxy for VC pairs' past success because we argue that, from both startups' and VCs' perspectives, going public is a stronger measure of successful exit than being acquired by another company. For startups that choose to go public, it indicates that they, as stand-alone firms, are more likely to have a strong edge in the product market and can fend for themselves (Bayar and Chemmanur (2011)). From VCs' point of view, going public could also be a more desirable exit choice compared to acquisition of their portfolio companies by others, as Sahlman (1990a) finds that VC investors earn the majority of their financial returns from portfolio companies that eventually go public.[8]

We hypothesize that the complementary skills and coordination efficiency (as proxied by the past success experience) between VC pairs is a potential channel through which the past collaboration between VC pairs affects the future success of startups. If a VC pair was able to help a previous startup they co-invested to go public, it is more likely that the VC pair has some complementary capabilities and can coordinate efficiently, such that together they could create greater value for future startups than other pairs of VC investors can. It is thus reasonable to expect that the VC pair could bring such complementarity into nurturing the current startup that they invest in. If

[8] In an untabulated analysis, we also define the past success of a VC pair as a startup backed by them going public or being acquired by another firm. The results remain consistent with what we show here in this subsection.

the complementary skills and coordination efficiency between VC investors (as proxied by their past success experience) is indeed one of the channels driving the results, we would expect to find that the future success of startups (as measured by exit, employment and sales growth, as well as innovation) is more pronounced in the sub-sample where VC investors share some successful experience in the past.

To empirically examine this channel, we use the following specification.

$$Y_{i,t} = \alpha + \beta \textit{Past Success}_{i,t} + \gamma Z_{i,t} + \textit{Industry}_j + \textit{Year}_t + \epsilon_{i,t}, \tag{6}$$

The dependent variable $Y_{i,t}$ denotes three sets of outcome variables we examine in our baseline results, which include successful exit, 3-year employment and sales growth, and innovation of startup i receiving its first VC investment in year t. The main independent variable of interest is *Past Success*$_{i,t}$. It is a dummy variable equal to one if the lead VC of startup i has past success experience with any syndicate member from the first round. It is equal to zero otherwise. We run the above specification for the sub-sample of startups that are backed by VCs with past collaboration experience (i.e., startups with *Past Collaboration* $= 1$). In other words, we would like to see the effect of *Past Success*$_{i,t}$ on future success of startups, conditional on VC investors having past collaboration experience. If the past success channel is valid, we would expect to find β to be positive and significant.

We report the corresponding results in Tables 13 to 15. Table 13 shows the results when the dependent variables represent successful exit of startups. In Column (1) where the successful exit of startups is measured by IPO or M&A, we find that the coefficient on *Past Success* is positive and statistically significant at 1% level. This indicates that, conditional on the sub-sample of startups with their VC investors collaborating in the past, the past success between lead VC investors and any syndicate members is still associated with higher probability of startups' exit. When we replace the dependent variable with IPO dummy in Column (2), the inference remains consistent. In Tables 14 and 15 where we regress the 3-year employment and sales growth or innovation output of startups on the *Past Success* variable, we document similar patterns: conditional on the sub-sample of startups with their VC investors having co-invested in the past, the past success between lead VC investors and any syndicate members is associated with higher employment and sales growth, higher probability of startups filing for new patents, and higher innovation quality of startups. Overall, these results together suggest that the effect of past collaboration of VCs on future success of startups is more concentrated in startups whose VC investors share the past success experience. This indicates that the complementary skills and coordination efficiency between VCs (as measured by past success of VC pairs) is indeed another channel driving our main results, which is consistent with the prediction of our testable hypothesis **H3**.

7 Conclusion

In this paper, we analyze the effect of the composition of venture capital (VC) syndicates on value creation to the entrepreneurial firms that they invest in. We hypothesize that VCs may learn about each other's skills at value creation when they co-invest together in an entrepreneurial firms, allowing for more efficient value creation when they co-invest in subsequent syndicates. Further, if VCs view syndication as a repeated game, this may generate incentives to co-operate to a greater extent with each other when investing together in a syndicate, reducing the probability of conflicts among VCs. We empirically analyze the implications of these hypotheses and find the following. First, prior collaboration between a lead VC and any of the VCs in a syndicate leads to greater short-term value creation, as evidenced by greater sales growth, employment growth, probability of a patented innovation, and the quality of innovations generated during the three years subsequent to VC syndicate investment. Second, prior collaboration between the lead VC and at least one of the members of the syndicate leads to greater long-term value creation, as evidenced by the higher probability of a successful exit (IPO or acquisition). Third, if the prior collaboration is very successful (leading to an IPO exit resulting from the previous collaboration), then there is even greater value creation by the VC syndicate compared to the case where the prior collaboration was less successful. Finally, consistent with prior collaboration allowing VCs to learn about each other's value creation skills and reducing potential conflicts among the VCs forming a syndicate, syndicates with prior collaboration between the lead VC and at least one syndicate member are characterized by more uniform syndicate compositions across financing rounds.

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Figure 1: Distribution of Distance Between Lead VC Investors and VC Syndicate Members

This graph plots the distribution of distance between lead VC investors and VC syndicate members from the first round of all startup companies. This measure is calculated as the distance between the MSAs of VC investors' headquarters. The unit of distance is in miles.

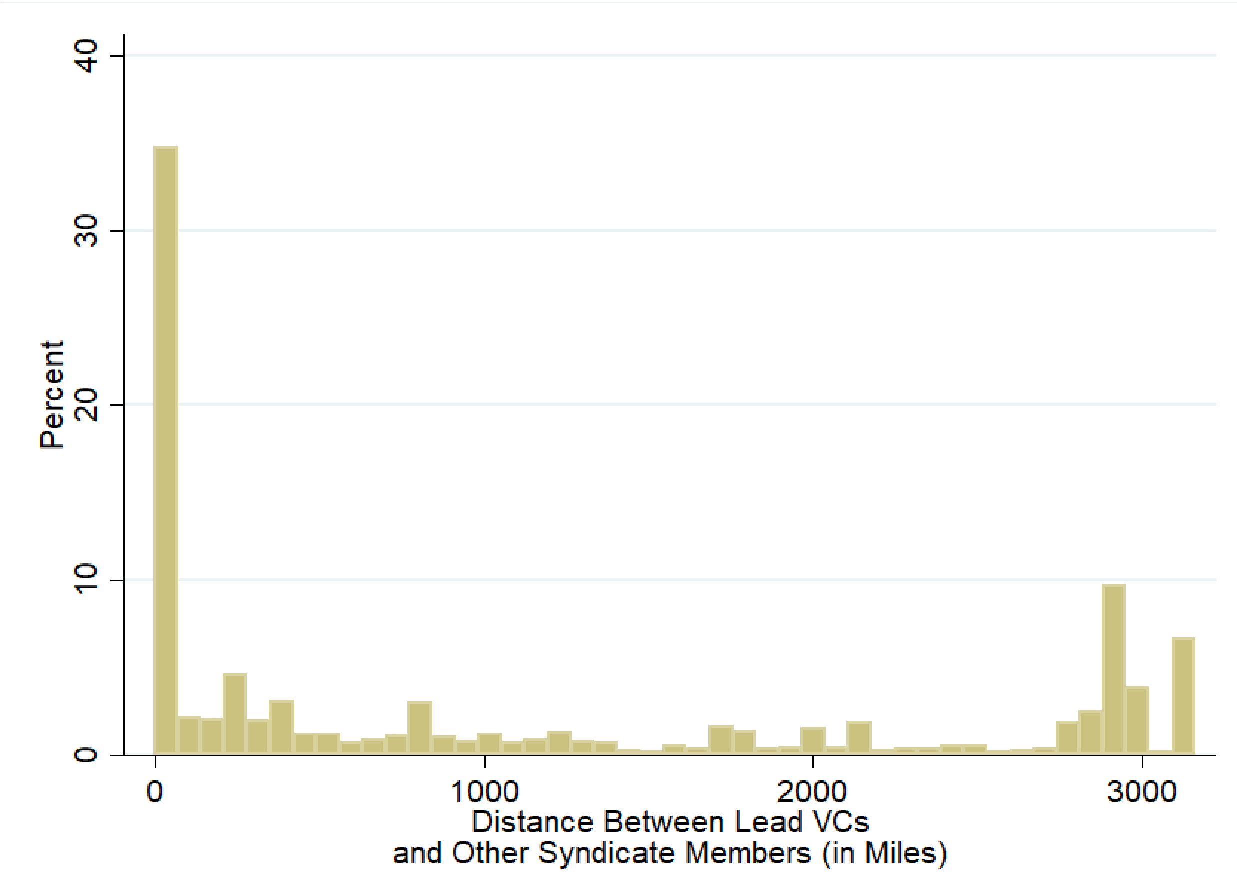

Table 1: Summary Statistics

This table reports the summary statistics of the variables used in our study. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *IPO or M&A* is a dummy variable equal to 1 if a startup exits via IPO or Mergers & Acquisitions (M&A); it is equal to 0 otherwise. *IPO* is a dummy variable equal to 1 if a startup exits via IPO only; it is equal to 0 otherwise. $\Delta\%$*Emp_3y* is the 3-year employment growth (in decimal term) of a startup starting from the year when it receives its first VC investment. $\Delta\%$*Sales_3y* is the 3-year sales growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *New_Pat_1_3* is an indicator variable equal to 1 if a startup files any new patents (that are eventually granted) from the year when it receives its first VC investment to 3 years after; it is equal to 0 otherwise. *CPP_1_3* is the average number of citations per patent of a startup from the year when it receives its first VC investment to 3 years after. It is constructed as the truncation-adjusted number of citations received by all the patents filed within this 3-year period divided by the truncation-adjusted number of patents filed during the same period. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. *Dist_Less_50* is the number of pairs between lead VC and any other syndicate members from the first round that has a distance less than 50 miles between the MSAs of their headquarters.

Variables	N	Mean	P25	Median	P75	S.D.
Past Collaboration	19,393	0.273	0.000	0.000	1.000	0.446
IPO or M&A	19,393	0.458	0.000	0.000	1.000	0.498
IPO	19,393	0.116	0.000	0.000	0.000	0.320
$\Delta\%$Emp_3y	5,009	1.396	0.000	0.060	1.231	3.151
$\Delta\%$Sales_3y	5,008	1.698	-0.053	0.136	1.264	4.159
New_Pat_1_3	19,393	0.193	0.000	0.000	0.000	0.395
CPP_1_3	19,393	0.142	0.000	0.000	0.000	0.368
Startup_Age	16,361	3.476	1.000	2.000	4.000	7.448
Emp	10,340	20.381	0.000	3.000	11.000	281.851
VC_Age	19,393	13.654	4.000	9.000	18.000	15.786
First_Round_Inv	18,482	9.377	2.000	4.500	9.900	27.832
Dist_Less_50	19,393	0.564	0.000	0.000	1.000	0.914

Table 2: Past VC Collaboration and Successful Startup Exit

This table reports the results of OLS regression of startups' exits on their VC investors' past collaboration. *IPO or M&A* is a dummy variable equal to 1 if a startup exits via IPO or Mergers & Acquisitions (M&A); it is equal to 0 otherwise. *IPO* is a dummy variable equal to 1 if a startup exits via IPO only; it is equal to 0 otherwise. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are excluded in columns (1) and (4) and are included in other specifications. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	IPO or M&A			IPO		
	(1)	(2)	(3)	(4)	(5)	(6)
Past Collaboration	0.0835***	0.0419***	0.0445***	0.0348***	0.0191**	0.0240***
	(0.0142)	(0.0084)	(0.0083)	(0.0083)	(0.0074)	(0.0066)
Startup_Age			-0.0016**			-0.0004
			(0.0007)			(0.0003)
Emp			0.0000			0.0000***
			(0.0000)			(0.0000)
VC_Age			0.0006*			0.0003
			(0.0003)			(0.0002)
First_Round_Inv			0.0012***			0.0010**
			(0.0004)			(0.0004)
Industry FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Adjusted R^2	0.0055	0.2382	0.1891	0.0021	0.1546	0.1322
Number of Obs.	17,360	17,358	8,196	17,360	17,358	8,196

Table 3: Past VC Collaboration and Startup Employment Growth

This table reports the results of OLS regression of startups' employment growth on their VC investors' past collaboration. $\Delta\%$*Emp_3y* is the 3-year employment growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are excluded in column (1) and are included in other specifications. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	$\Delta\%$Emp_3y		
	(1)	(2)	(3)
Past Collaboration	0.0989***	0.1012***	0.0866***
	(0.0099)	(0.0146)	(0.0217)
Startup_Age			-0.0187***
			(0.0050)
Emp			-0.0004**
			(0.0002)
VC_Age			0.0049*
			(0.0025)
First_Round_Inv			0.0075*
			(0.0043)
Industry FE	No	Yes	Yes
Year FE	No	Yes	Yes
Adjusted R^2	0.0000	0.0177	0.0268
Number of Obs.	4,744	4,734	4,111

Table 4: Past VC Collaboration and Startup Sales Growth

This table reports the results of OLS regression of startups' sales growth on their VC investors' past collaboration. $\Delta\%$*Sales_3y* is the 3-year sales growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are excluded in column (1) and are included in other specifications. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	$\Delta\%$Sales_3y		
	(1)	(2)	(3)
Past Collaboration	0.1049*	0.1212	0.1317***
	(0.0535)	(0.0816)	(0.0359)
Startup_Age			-0.0186**
			(0.0083)
Emp			-0.0005***
			(0.0002)
VC_Age			0.0080***
			(0.0028)
First_Round_Inv			0.0122**
			(0.0059)
Industry FE	No	Yes	Yes
Year FE	No	Yes	Yes
Adjusted R^2	0.0001	0.0157	0.0242
Number of Obs.	4,743	4,733	4,110

Table 5: Past VC Collaboration and Probability of Startup Successful Innovation

This table reports the results of OLS regression of startups' filing of new patents on their VC investors' past collaboration. *New_Pat_1_3* is an indicator variable equal to 1 if a startup files any new patents (that are eventually granted) from the year when it receives its first VC investment to 3 years after; it is equal to 0 otherwise. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are excluded in column (1) and are included in other specifications. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	New_Pat_1_3		
	(1)	(2)	(3)
Past Collaboration	0.0665***	0.0473***	0.0400***
	(0.0113)	(0.0077)	(0.0073)
Startup_Age			-0.0046***
			(0.0005)
Emp			0.0000
			(0.0000)
VC_Age			0.0010***
			(0.0003)
First_Round_Inv			0.0005**
			(0.0002)
Industry FE	No	Yes	Yes
Year FE	No	Yes	Yes
Adjusted R^2	0.0054	0.1398	0.1463
Number of Obs.	17,360	17,358	8,196

Table 6: Past VC Collaboration and Startup Innovation Quality

This table reports the results of OLS regression of startups' innovation quality (as measured by the number of citations per patent) on their VC investors' past collaboration. *CPP_1_3* is the average number of citations per patent of a startup from the year when it receives its first VC investment to 3 years after. It is constructed as the truncation-adjusted number of citations received by all the patents filed within this 3-year period divided by the truncation-adjusted number of patents filed during the same period. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are excluded in column (1) and are included in other specifications. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	CPP_1_3		
	(1)	(2)	(3)
Past Collaboration	0.0626***	0.0463***	0.0400***
	(0.0131)	(0.0101)	(0.0108)
Startup_Age			-0.0045***
			(0.0006)
Emp			-0.0000
			(0.0000)
VC_Age			0.0006**
			(0.0003)
First_Round_Inv			0.0004**
			(0.0002)
Industry FE	No	Yes	Yes
Year FE	No	Yes	Yes
Adjusted R^2	0.0054	0.1047	0.1113
Number of Obs.	17,360	17,358	8,196

Table 7: IV Analysis: Past VC Collaboration and Successful Startup Exit

This table reports the results of IV regression of startups' exits on their VC investors' past collaboration. We instrument the *Past Collaboration* with *Dist_Less_50*, which is constructed, for each startup, as the number of pairs between lead VC and any other syndicate members from the first round that has a distance less than 50 miles between the MSAs of their headquarters. *IPO or M&A* is a dummy variable equal to 1 if a startup exits via IPO or Mergers & Acquisitions (M&A); it is equal to 0 otherwise. *IPO* is a dummy variable equal to 1 if a startup exits via IPO only; it is equal to 0 otherwise. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Past Collaboration	IPO or M&A	Past Collaboration	IPO
	(1)	(2)	(3)	(4)
Dist_Less_50	0.1042***		0.1042***	
	(0.0083)		(0.0083)	
Past Collaboration		0.1680**		0.0658**
		(0.0740)		(0.0293)
Startup_Age	-0.0039***	-0.0009	-0.0039***	-0.0002
	(0.0005)	(0.0008)	(0.0005)	(0.0004)
Emp	0.0000	0.0000	0.0000	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
VC_Age	0.0044***	-0.0000	0.0044***	0.0001
	(0.0001)	(0.0006)	(0.0001)	(0.0002)
First_Round_Inv	0.0005**	0.0011**	0.0005**	0.0010**
	(0.0002)	(0.0004)	(0.0002)	(0.0004)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.0926	–	0.0926	–
Number of Obs.	8,196	8,196	8,196	8,196
Kleibergen-Paap rk Wald F stat	159.16		159.16	

Table 8: IV Analysis: Past VC Collaboration and Startup Employment Growth

This table reports the results of IV regression of startups' employment growth on their VC investors' past collaboration. We instrument the *Past Collaboration* with *Dist_Less_50*, which is constructed, for each startup, as the number of pairs between lead VC and any other syndicate members from the first round that has a distance less than 50 miles between the MSAs of their headquarters. $\Delta\%$*Emp_3y* is the 3-year employment growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Past Collaboration	$\Delta\%$Emp_3y
	(1)	(2)
Dist_Less_50	0.1076***	
	(0.0138)	
Past Collaboration		0.5763***
		(0.1158)
Startup_Age	-0.0031***	-0.0166***
	(0.0010)	(0.0058)
Emp	-0.0000	-0.0004**
	(0.0000)	(0.0002)
VC_Age	0.0043***	0.0027
	(0.0002)	(0.0031)
First_Round_Inv	0.0010*	0.0070
	(0.0005)	(0.0044)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.0854	–
Number of Obs.	4,111	4,111
Kleibergen-Paap rk Wald F stat	61.13	

Table 9: IV Analysis: Past VC Collaboration and Startup Sales Growth

This table reports the results of IV regression of startups' sales growth on their VC investors' past collaboration. We instrument the *Past Collaboration* with *Dist_Less_50*, which is constructed, for each startup, as the number of pairs between lead VC and any other syndicate members from the first round that has a distance less than 50 miles between the MSAs of their headquarters. $\Delta\%$*Sales_3y* is the 3-year sales growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Past Collaboration	$\Delta\%$Sales_3y
	(1)	(2)
Dist_Less_50	0.1075***	
	(0.0138)	
Past Collaboration		1.0365***
		(0.3251)
Startup_Age	-0.0031***	-0.0148*
	(0.0010)	(0.0087)
Emp	-0.0000	-0.0005***
	(0.0000)	(0.0002)
VC_Age	0.0043***	0.0039
	(0.0002)	(0.0040)
First_Round_Inv	0.0010*	0.0113*
	(0.0005)	(0.0061)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.0852	–
Number of Obs.	4,110	4,110
Kleibergen-Paap rk Wald F stat	61.52	

Table 10: IV Analysis: Past VC Collaboration and Probability of Startup Successful Innovation

This table reports the results of IV regression of startups' filing of new patents on their VC investors' past collaboration. We instrument the *Past Collaboration* with *Dist_Less_50*, which is constructed, for each startup, as the number of pairs between lead VC and any other syndicate members from the first round that has a distance less than 50 miles between the MSAs of their headquarters. *New_Pat_1_3* is an indicator variable equal to 1 if a startup files any new patents (that are eventually granted) from the year when it receives its first VC investment to 3 years after; it is equal to 0 otherwise. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Past Collaboration	New_Pat_1_3
	(1)	(2)
Dist_Less_50	0.1042***	
	(0.0083)	
Past Collaboration		0.1770***
		(0.0361)
Startup_Age	-0.0039***	-0.0039***
	(0.0005)	(0.0005)
Emp	0.0000	0.0000
	(0.0000)	(0.0000)
VC_Age	0.0044***	0.0003
	(0.0001)	(0.0004)
First_Round_Inv	0.0005**	0.0005**
	(0.0002)	(0.0002)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.0926	–
Number of Obs.	8,196	8,196
Kleibergen-Paap rk Wald F stat	159.16	

Table 11: IV Analysis: Past VC Collaboration and Startup Innovation Quality

This table reports the results of IV regression of startups' innovation quality on their VC investors' past collaboration. We instrument the *Past Collaboration* with *Dist_Less_50*, which is constructed, for each startup, as the number of pairs between lead VC and any other syndicate members from the first round that has a distance less than 50 miles between the MSAs of their headquarters. *CPP_1_3* is the average number of citations per patent of a startup from the year when it receives its first VC investment to 3 years after. It is constructed as the truncation-adjusted number of citations received by all the patents filed within this 3-year period divided by the truncation-adjusted number of patents filed during the same period. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Past Collaboration	CPP_1_3
	(1)	(2)
Dist_Less_50	0.1042***	
	(0.0083)	
Past Collaboration		0.1409***
		(0.0157)
Startup_Age	-0.0039***	-0.0039***
	(0.0005)	(0.0006)
Emp	0.0000	-0.0000
	(0.0000)	(0.0000)
VC_Age	0.0044***	0.0001
	(0.0001)	(0.0003)
First_Round_Inv	0.0005**	0.0004**
	(0.0002)	(0.0002)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.0926	–
Number of Obs.	8,196	8,196
Kleibergen-Paap rk Wald F stat	159.16	

Table 12: VCs' Past Collaboration and Composition of VC Syndicates

This table reports the results of OLS regression of VC composition on VC investors' past collaboration. *VC_Comp* is constructed as $(\sum_{i=1}^{N}\sum_{r=1}^{R} VC_{i,r})/(Num\_VC \times Num\_Rounds)$, where $VC_{i,r}$ in the numerator denotes VC i investing in round r. We count the number of rounds in which each VC investor participates, and we then aggregate this across all the VC investors in different rounds. Num_VC in the denominator denotes the number of VC investors across all financing rounds. Num_Rounds in the denominator denotes the number of financing rounds a startup receives. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are excluded in column (1) and are included in other specifications. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	VC_Comp		
	(1)	(2)	(3)
Past Collaboration	0.0099**	0.0125***	0.0205***
	(0.0038)	(0.0039)	(0.0041)
Startup_Age			0.0025***
			(0.0002)
Emp			0.0000
			(0.0000)
VC_Age			-0.0002
			(0.0002)
First_Round_Inv			-0.0002**
			(0.0001)
Industry FE	No	Yes	Yes
Year FE	No	Yes	Yes
Adjusted R^2	0.0004	0.0521	0.0741
Number of Obs.	11,631	11,628	6,306

Table 13: Past VC Collaboration, VCs' Past Syndicate Success, and Successful Startup Exit

This table reports the results of OLS regression of startups' exits on their VC investors' past success, conditional on the subsample of startups where the VC investors from the first round have co-invested in the past. *IPO or M&A* is a dummy variable equal to 1 if a startup exits via IPO or Mergers & Acquisitions (M&A); it is equal to 0 otherwise. *IPO* is a dummy variable equal to 1 if a startup exits via IPO only; it is equal to 0 otherwise. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Past Success* is an indicator variable equal to 1 if at least one pair between the lead VC investor and any other syndicate members from the first round has previously brought a startup into IPO; it is equal to 0 otherwise. *Startup_Age* is the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	IPO or M&A	IPO
	(1)	(2)
	(Past Collaboration = 1)	
Past Success	0.0628***	0.0595***
	(0.0098)	(0.0180)
Startup_Age	-0.0039**	-0.0019***
	(0.0015)	(0.0006)
Emp	0.0000	0.0001***
	(0.0000)	(0.0000)
VC_Age	0.0007	0.0003
	(0.0006)	(0.0003)
First_Round_Inv	0.0007**	0.0006*
	(0.0003)	(0.0003)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.1764	0.1475
Number of Obs.	2,344	2,344

Table 14: Past VC Collaboration, VCs' Past Syndicate Success, and Startup Employment and Sales Growth

This table reports the results of OLS regression of startups' employment and sales growth on their VC investors' past success, conditional on the subsample of startups where the VC investors from the first round have co-invested in the past. $\Delta\%$*Emp_3y* is the 3-year employment growth (in decimal term) of a startup starting from the year when it receives its first VC investment. $\Delta\%$*Sales_3y* is the 3-year sales growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Past Success* is an indicator variable equal to 1 if at least one pair between the lead VC investor and any other syndicate members from the first round has previously brought a startup into IPO; it is equal to 0 otherwise. *Startup_Age* is the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	$\Delta\%$Emp_3y	$\Delta\%$Sales_3y
	(1)	(2)
	(Past Collaboration = 1)	
Past Success	0.2447***	0.2714**
	(0.0873)	(0.1288)
Startup_Age	-0.0566***	-0.0694***
	(0.0094)	(0.0147)
Emp	-0.0006***	-0.0007***
	(0.0001)	(0.0002)
VC_Age	-0.0022	-0.0013
	(0.0081)	(0.0085)
First_Round_Inv	0.0080***	0.0128**
	(0.0026)	(0.0050)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.0220	0.0261
Number of Obs.	1,172	1,171

Table 15: Past VC Collaboration, VCs' Past Syndicate Success, and Startup Innovation

This table reports the results of OLS regression of startups' innovation capacity on their VC investors' past success, conditional on the subsample of startups where the VC investors from the first round have co-invested in the past. *New_Pat_1_3* is an indicator variable equal to 1 if a startup files any new patents (that are eventually granted) from the year when it receives its first VC investment to 3 years after; it is equal to 0 otherwise. *CPP_1_3* is the truncation-adjusted number of citations received by all the patents of a startup filed within 3-year period after the first investment divided by the truncation-adjusted number of patents filed during the same period. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Past Success* is an indicator variable equal to 1 if at least one pair between the lead VC investor and any other syndicate members from the first round has previously brought a startup into IPO; it is equal to 0 otherwise. *Startup_Age* is the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	New_Pat_1_3	CPP_1_3
	(1)	(2)
	(Past Collaboration = 1)	
Past Success	0.0686***	0.0746***
	(0.0162)	(0.0205)
Startup_Age	-0.0047**	-0.0062***
	(0.0019)	(0.0016)
Emp	0.0001***	0.0000***
	(0.0000)	(0.0000)
VC_Age	0.0009*	0.0005
	(0.0005)	(0.0006)
First_Round_Inv	0.0008***	0.0007***
	(0.0001)	(0.0001)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.1449	0.1160
Number of Obs.	2,344	2,344

Appendices

Table A.1: Past VC Collaboration and Successful Startup Exit: Continuous Measure of Past Collaboration

This table reports the robustness checks of baseline OLS regression of startups' exits on their VC investors' past collaboration using a continuous measure of VCs' past collaboration (instead of a dummy variable). *IPO or M&A* is a dummy variable equal to 1 if a startup exits via IPO or Mergers & Acquisitions (M&A); it is equal to 0 otherwise. *IPO* is a dummy variable equal to 1 if a startup exits via IPO only; it is equal to 0 otherwise. *Num of Collaboration* is the natural logarithm of 1 plus the average number of past collaborations (i.e., number of prior co-investments) between the lead VC investor of a startup and any other syndicate members from the first round. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	IPO or M&A	IPO
	(1)	(2)
Num of Collaboration	0.0501***	0.0384***
	(0.0124)	(0.0092)
Startup_Age	-0.0016**	-0.0004
	(0.0007)	(0.0003)
Emp	0.0000	0.0000***
	(0.0000)	(0.0000)
VC_Age	0.0005	0.0002
	(0.0003)	(0.0002)
First_Round_Inv	0.0012***	0.0010**
	(0.0004)	(0.0004)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.1888	0.1330
Number of Obs.	8,196	8,196

Table A.2: Past VC Collaboration and Startup Employment and Sales Growth: Continuous Measure of Past Collaboration

This table reports the robustness checks of baseline OLS regression of startups' employment and sales growth on their VC investors' past collaboration using a continuous measure of VCs' past collaboration (instead of a dummy variable). $\Delta\%$*Emp_3y* is the 3-year employment growth (in decimal term) of a startup starting from the year when it receives its first VC investment. $\Delta\%$*Sales_3y* is the 3-year sales growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Num of Collaboration* is the natural logarithm of 1 plus the average number of past collaborations (i.e., number of prior co-investments) between the lead VC investor of a startup and any other syndicate members from the first round. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	$\Delta\%$Emp_3y	$\Delta\%$Sales_3y
	(1)	(2)
Num of Collaboration	0.1211	0.2164**
	(0.0729)	(0.0983)
Startup_Age	-0.0187***	-0.0185**
	(0.0049)	(0.0078)
Emp	-0.0004**	-0.0005***
	(0.0002)	(0.0002)
VC_Age	0.0048*	0.0077**
	(0.0026)	(0.0031)
First_Round_Inv	0.0075*	0.0122**
	(0.0043)	(0.0059)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.0268	0.0244
Number of Obs.	4,111	4,110

Table A.3: Past VC Collaboration and Startup Innovation: Continuous Measure of Past Collaboration

This table reports the robustness checks of baseline OLS regression of startups' innovation capacity on their VC investors' past collaboration using a continuous measure of VCs' past collaboration (instead of a dummy variable). *New_Pat_1_3* is an indicator variable equal to 1 if a startup files any new patents (that are eventually granted) from the year when it receives its first VC investment to 3 years after; it is equal to 0 otherwise. *CPP_1_3* is the truncation-adjusted number of citations received by all the patents filed by a startup within 3-year period after the first investment divided by the truncation-adjusted number of patents filed during the same period. *Num of Collaboration* is the natural logarithm of 1 plus the number of past collaborations (i.e., number of prior co-investments) between the lead VC investor of a startup and any other syndicate members from the first round. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	New_Pat_1_3	CPP_1_3
	(1)	(2)
Num of Collaboration	0.0510***	0.0456***
	(0.0141)	(0.0152)
Startup_Age	-0.0046***	-0.0045***
	(0.0005)	(0.0006)
Emp	0.0000	0.0000
	(0.0000)	(0.0000)
VC_Age	0.0009***	0.0006**
	(0.0003)	(0.0002)
First_Round_Inv	0.0005**	0.0005**
	(0.0002)	(0.0002)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.1463	0.1109
Number of Obs.	8,196	8,196

Table A.4: Past VC Collaboration and Successful Startup Exit

This table reports the robustness checks of baseline OLS regression of startups' exits on their VC investors' past collaboration, conditional on the subsample of startups where we exclude startups in San Francisco/New York/Boston areas. *IPO or M&A* is a dummy variable equal to 1 if a startup exits via IPO or Mergers & Acquisitions (M&A); it is equal to 0 otherwise. *IPO* is a dummy variable equal to 1 if a startup exits via IPO only; it is equal to 0 otherwise. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	IPO or M&A	IPO
	(1)	(2)
Past Collaboration	0.0435***	0.0290***
	(0.0106)	(0.0070)
Startup_Age	-0.0014*	-0.0004
	(0.0007)	(0.0004)
Emp	0.0000	0.0000**
	(0.0000)	(0.0000)
VC_Age	0.0005	0.0003
	(0.0003)	(0.0002)
First_Round_Inv	0.0011**	0.0010**
	(0.0005)	(0.0004)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.1825	0.1349
Number of Obs.	6,453	6,453

Table A.5: Past VC Collaboration and Startup Employment and Sales Growth

This table reports the robustness checks of baseline OLS regression of startups' employment and sales growth on their VC investors' past collaboration, conditional on the subsample of startups where we exclude startups in San Francisco/New York/Boston areas. $\Delta\%$*Emp_3y* is the 3-year employment growth (in decimal term) of a startup starting from the year when it receives its first VC investment. $\Delta\%$*Sales_3y* is the 3-year sales growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	$\Delta\%$Emp_3y	$\Delta\%$Sales_3y
	(1)	(2)
Past Collaboration	0.0789*	0.1678
	(0.0423)	(0.1163)
Startup_Age	-0.0145***	-0.0123
	(0.0049)	(0.0086)
Emp	-0.0004***	-0.0006***
	(0.0001)	(0.0001)
VC_Age	0.0075***	0.0130***
	(0.0022)	(0.0027)
First_Round_Inv	0.0069	0.0113*
	(0.0041)	(0.0057)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.0270	0.0250
Number of Obs.	3,216	3,215

Table A.6: Past VC Collaboration and Startup Innovation

This table reports the robustness checks of baseline OLS regression of startups' innovation capacity on their VC investors' past collaboration, conditional on the subsample of startups where we exclude startups in San Francisco/New York/Boston areas. *New_Pat_1_3* is an indicator variable equal to 1 if a startup files any new patents (that are eventually granted) from the year when it receives its first VC investment to 3 years after; it is equal to 0 otherwise. *CPP_1_3* is the truncation-adjusted number of citations received by all the patents filed by a startup within 3-year period after the first investment divided by the truncation-adjusted number of patents filed during the same period. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	New_Pat_1_3	CPP_1_3
	(1)	(2)
Past Collaboration	0.0423***	0.0470***
	(0.0093)	(0.0120)
Startup_Age	-0.0051***	-0.0048***
	(0.0007)	(0.0006)
Emp	0.0000	0.0000
	(0.0000)	(0.0000)
VC_Age	0.0010**	0.0006
	(0.0004)	(0.0004)
First_Round_Inv	0.0003*	0.0003*
	(0.0002)	(0.0002)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.1495	0.1062
Number of Obs.	6,453	6,453

Table A.7: Past VC Collaboration and Successful Startup Exit: IV Analysis Using Different Distance Cutoff Points

This table reports the robustness checks of IV regression of startups' exits on their VC investors' past collaboration. We instrument the *Past Collaboration* with variables using different distance cutoff points. For example, *Dist_Less_25* is the number of pairs between the lead VC of a startup and any other syndicate members from the first round that has a distance less than 25 miles between the MSAs of their headquarters. *IPO or M&A* is a dummy variable equal to 1 if a startup exits via IPO or Mergers & Acquisitions (M&A). *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round. All other control variables are defined similarly as in previous tables. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Panel A: First-stage regressions				
	Past Collaboration			
	(1)	(2)	(3)	(4)
Dist_Less_25	0.1037***			
	(0.0101)			
Dist_Less_100		0.1027***		
		(0.0076)		
Dist_Less_150			0.0998***	
			(0.0077)	
Dist_Less_200				0.0988***
				(0.0083)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.0772	0.0926	0.0907	0.0906
Number of Obs.	8,196	8,196	8,196	8,196
Kleibergen-Paap rk Wald F stat	107.23	186.41	172.02	144.64
Panel B: Second-stage regressions				
	IPO or M&A			
	(1)	(2)	(3)	(4)
Past Collaboration (Dist_Less_25)	0.1329*			
	(0.0759)			
Past Collaboration (Dist_Less_100)		0.1745**		
		(0.0716)		
Past Collaboration (Dist_Less_150)			0.1511**	
			(0.0722)	
Past Collaboration (Dist_Less_200)				0.1564**
				(0.0680)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	–	–	–	–
Number of Obs.	8,196	8,196	8,196	8,196

Table A.8: Past VC Collaboration and Startup Employment Growth: IV Analysis Using Different Distance Cutoff Points

This table reports the robustness checks of IV regression of startups' employment growth on their VC investors' past collaboration. We instrument the *Past Collaboration* with variables using different distance cutoff points. For example, *Dist_Less_25* is the number of pairs between the lead VC of a startup and any other syndicate members from the first round that has a distance less than 25 miles between the MSAs of their headquarters. $\Delta\%$*Emp_3y* is the 3-year employment growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round. All other control variables are defined similarly as in previous tables. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Panel A: First-stage regressions				
	Past Collaboration			
	(1)	(2)	(3)	(4)
Dist_Less_25	0.1167***			
	(0.0170)			
Dist_Less_100		0.1070***		
		(0.0123)		
Dist_Less_150			0.1037***	
			(0.0116)	
Dist_Less_200				0.1023***
				(0.0123)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.0747	0.0859	0.0840	0.0840
Number of Obs.	4,111	4,111	4,111	4,111
Kleibergen-Paap rk Wald F stat	47.67	76.47	80.78	69.73
Panel B: Second-stage regressions				
	$\Delta\%$Emp_3y			
	(1)	(2)	(3)	(4)
Past Collaboration (Dist_Less_25)	0.8038			
	(–)			
Past Collaboration (Dist_Less_100)		0.5386		
		(–)		
Past Collaboration (Dist_Less_150)			0.4718	
			(–)	
Past Collaboration (Dist_Less_200)				0.4298
				(–)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	–	–	–	–
Number of Obs.	4,111	4,111	4,111	4,111

Table A.9: Past VC Collaboration and Startup Sales Growth: IV Analysis Using Different Distance Cutoff Points

This table reports the robustness checks of IV regression of startups' sales growth on their VC investors' past collaboration. We instrument the *Past Collaboration* with variables using different distance cutoff points. For example, *Dist_Less_25* is the number of pairs between the lead VC of a startup and any other syndicate members from the first round that has a distance less than 25 miles between the MSAs of their headquarters. $\Delta\%$*Sales_3y* is the 3-year sales growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round. All other control variables are defined similarly as in previous tables. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Panel A: First-stage regressions				
	Past Collaboration			
	(1)	(2)	(3)	(4)
Dist_Less_25	0.1165***			
	(0.0169)			
Dist_Less_100		0.1070***		
		(0.0123)		
Dist_Less_150			0.1036***	
			(0.0116)	
Dist_Less_200				0.1022***
				(0.0123)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.0745	0.0858	0.0839	0.0839
Number of Obs.	4,110	4,110	4,110	4,110
Kleibergen-Paap rk Wald F stat	47.94	76.99	81.31	70.12
Panel B: Second-stage regressions				
	$\Delta\%$Sales_3y			
	(1)	(2)	(3)	(4)
Past Collaboration (Dist_Less_25)	1.5206***			
	(0.3225)			
Past Collaboration (Dist_Less_100)		0.9842***		
		(0.3356)		
Past Collaboration (Dist_Less_150)			0.8735*	
			(0.4262)	
Past Collaboration (Dist_Less_200)				0.9132**
				(0.3546)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	–	–	–	–
Number of Obs.	4,110	4,110	4,110	4,110

Table A.10: Past VC Collaboration and Probability of Startup Successful Innovation: IV Analysis Using Different Distance Cutoff Points

This table reports the robustness checks of IV regression of startups' filing of new patents on their VC investors' past collaboration. We instrument the *Past Collaboration* with variables using different distance cutoff points. For example, *Dist_Less_25* is the number of pairs between the lead VC of a startup and any other syndicate members from the first round that has a distance less than 25 miles between the MSAs of their headquarters. *New_Pat_1_3* is an indicator variable equal to 1 if a startup files any new patents (that are eventually granted) from the year when it receives its first VC investment to 3 years after. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round. All other control variables are defined similarly as in previous tables. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Panel A: First-stage regressions				
	Past Collaboration			
	(1)	(2)	(3)	(4)
Dist_Less_25	0.1037***			
	(0.0101)			
Dist_Less_100		0.1027***		
		(0.0076)		
Dist_Less_150			0.0998***	
			(0.0077)	
Dist_Less_200				0.0988***
				(0.0083)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.0772	0.0926	0.0907	0.0906
Number of Obs.	8,196	8,196	8,196	8,196
Kleibergen-Paap rk Wald F stat	107.23	186.41	172.02	144.64
Panel B: Second-stage regressions				
	New_Pat_1_3			
	(1)	(2)	(3)	(4)
Past Collaboration (Dist_25)	0.0871			
	(0.0648)			
Past Collaboration (Dist_100)		0.1511***		
		(0.0375)		
Past Collaboration (Dist_150)			0.1442***	
			(0.0405)	
Past Collaboration (Dist_200)				0.1298***
				(0.0462)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	–	–	–	–
Number of Obs.	8,196	8,196	8,196	8,196

Table A.11: Past VC Collaboration and Startup Innovation Quality: IV Analysis Using Different Distance Cutoff Points

This table reports the robustness checks of IV regression of startups' innovation quality on their VC investors' past collaboration. We instrument the *Past Collaboration* with variables using different distance cutoff points. For example, *Dist_Less_25* is the number of pairs between the lead VC of a startup and any other syndicate members from the first round that has a distance less than 25 miles between MSAs of their headquarters. *CPP_1_3* is truncation-adjusted number of citations received by all patents filed by a startup within 3-year period after first investment divided by the truncation-adjusted number of patents filed during the same period. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round. All other control variables are defined similarly as in previous tables. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Panel A: First-stage regressions				
	Past Collaboration			
	(1)	(2)	(3)	(4)
Dist_Less_25	0.1037***			
	(0.0101)			
Dist_Less_100		0.1027***		
		(0.0076)		
Dist_Less_150			0.0998***	
			(0.0077)	
Dist_Less_200				0.0988***
				(0.0083)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.0772	0.0926	0.0907	0.0906
Number of Obs.	8,196	8,196	8,196	8,196
Kleibergen-Paap rk Wald F stat	107.23	186.41	172.02	144.64
Panel B: Second-stage regressions				
	CPP_1_3			
	(1)	(2)	(3)	(4)
Past Collaboration (Dist_Less_25)	0.0992**			
	(0.0428)			
Past Collaboration (Dist_Less_100)		0.1312***		
		(0.0200)		
Past Collaboration (Dist_Less_150)			0.1270***	
			(0.0230)	
Past Collaboration (Dist_Less_200)				0.1086***
				(0.0283)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	–	–	–	–
Number of Obs.	8,196	8,196	8,196	8,196