Two's company, three's a crowd
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This paper examines how the number, quality, and depth of the relationships, between a corporate venture capital (CVC) unit and the traditional venture capital (VC) that it coinvests with, affect the corporate investor’s innovation performance. We find that there is an inverted U-shaped relationship between the number and the quality of the CVC unit’s partners and the corporate investor’s innovation performance. The depth of the relationship weakens the diminishing benefits of coinvesting with many partners. Jointly, our findings illustrate the danger of the ‘more is always better’ principle in terms of VC centrality and provide in-depth insights for corporate investors to organize innovation.
innovation performance. We suggest that this is true irrespective of the quality of the VC partner that the CVC firm is investing with.

Research also suggests, however, that the depth of these relationships matters too. Deeper relationships, which are built by frequent interactions, allow partners to build trust (Carson et al., 2003; Gulati, 1995) and relational capital, which improves communication (Larsson et al., 1998; Poppo & Zenger, 2002) and facilitates the exchange of information. Frequent interactions also lead to the development of what has been termed ‘partner-specific absorptive capacity’ (Dyer & Singh, 1998), which increases the firm’s ability to work with its partner. In our context, the implication is that the depth of the relationship can reduce the costs that come from having too many partners. Put another way, the depth of the relationship should moderate the inverted U-shaped relationship between the CVCs unit’s centrality in the syndicated network and the corporate investor’s innovation performance. Again, we suggest that this is true irrespective of the quality of the CVC units’ partners.

Empirically, we test our proposed hypotheses using panel data on the corporate investors of 58 pharmaceutical firms over the period 2002–2016. We use degree centrality to describe the number of partners, eigenvector centrality to account for quality, and tie strength to measure the depth of the relationship. Our findings largely support our hypotheses. We show that there is an inverted U-shaped relationship between syndicated network centrality and corporate innovative performance. We show that being too central can be as bad as being too peripheral and suggest that firms can maximize their innovation performance by choosing a modest number of partners. Interestingly, we find that the depth of the partnership reduces both the benefits and costs of degree centrality but has no effect on eigenvector centrality.

In so doing, we make a number of clear contributions to the emerging body of literature on the relationship between the network position of CVC units and corporate investors’ innovation performance. First, we are, to the best of our knowledge, the first to consider the way in which CVC units interact with their VC partners (i.e., traditional VCs) in a syndication network, in terms of innovation performance. Second, we move the discussion forward, from one of the simple linear relationships, by showing that there is a curvilinear relationship between financing social network position and innovation performance. Finally, we contribute by illustrating that tie strength between CVC units and their partners can weaken the innovation performance of corporate investors. From a practical perspective, our findings provide managers with actionable advice on how to choose, operate, and interact with their partners when engaging in syndication activities for corporate innovation.

2 | THEORY AND HYPOTHESES

2.1 | Background

Innovation plays a vital role in gaining a competitive advantage and achieving the rapid growth of high-tech firms (Dong et al., 2017; Zheng & Yang, 2015). In technology-intensive industries, established firms often, however, have neither the time nor the technology diversity (Dong et al., 2017; Yan et al., 2020), necessary to sustain a continuous innovation process (Cohen & Levinthal, 1990). Consequently, established firms often search for novel elements inputs beyond organizational boundaries to achieve higher innovation performance.

CVC investments are one commonly used tool for accessing externally created knowledge. CVC investments are typically made by established firms (i.e., corporate investors) to (1) access and learn the new technology knowledge and (2) get inspiration to develop complementary or alternative technology or products (Kang, 2019). And research shows that CVC works. Research shows that corporate investors, which engage in CVC, gain a ‘window’ on new technology and knowledge (Dushnitsky & Lenox, 2005; Wadhwa & Kotha, 2006), which leads to the development of new products (Smith & Shah, 2013) and higher innovation rates (Chenmanur et al., 2014; Dushnitsky & Lenox, 2005; Wadhwa & Kotha, 2006).

Most CVC units do not invest alone but instead coinvest—or syndicate—with traditional VCs (Zhang et al., 2021), such as independent venture capital (IVC) firms. The two pursue different investment goals but cooperate in a mutually beneficial way. Traditional VCs, for example, tend to care more about financial returns (Gompers, 2002). They tend also to push entrepreneurs to develop new products, as quickly as possible, to assure a successful exit at a great return (Gompers, 2002). Because of this, CVC units can rely on traditional VCs to identify promising and high-quality targets. At the same time, CVC can provide investees with complementary assets, which increase the likelihood that the venture succeeds commercially. Thus, there are mutually beneficial reasons for CVC units to syndicate their investments with traditional VCs.

By coinvesting, however, CVC firms create or join the syndication networks. Research has long highlighted the importance of network position (e.g., Zhang et al., 2021). Most scholars, however, pay much attention to the positive effect of centrality and although scholars have investigated the negative effects of centrality (e.g., Dong et al., 2017; Dong & Yang, 2016), we know little about the negative effects of networks in the VC context. In this paper, we make a first step towards rectifying that. We explore the positive and negative effects of the CVCs’ position in the VC syndication networks, in terms of (1) the quantity of its VC partners, (2) the quality of its VC partners, and (3) the depth of its relationship with its partners.

2.2 | Hypotheses

2.2.1 | The number of partners

Degree centrality considers the total count of ties of an actor in the network (Freeman, 1979). It is the most widely used centrality measure (Salman & Saives, 2005). We consider CVC units and other traditional VCs as constituting the venture capital syndication networks. And we define degree centrality in terms of the number of partners:
the more partners a focal (C)VC has, the more central it is in the VC syndication networks.

We propose that the CVC which has higher levels of degree centrality in the venture capital syndication networks will enjoy the greatest benefits, for two reasons. First, traditional VCs can help CVC units to identify the most promising ventures in which their corporate investors can attain novel technology, knowledge, and information. The more partners the CVC unit has, the more opportunities to get access to promising ventures. In this way, the central CVC unit can assimilate more novel knowledge, technology, and information and recombine all of them with what they already own. This will enhance the corporate investor’s innovation performance.

Second, the premise of syndication is that traditional VCs expect corporate investors to offer investee ventures complementary resources to pursue financial returns and therefore enhance the likelihood of successful exit (Kang, 2019). The more partners the CVC has, the more capacity for it to create value with investee ventures, which facilitates the traditional VCs’ exit on the one hand, as well as the corporate investors’ innovative performance on the other.

A high level of degree centrality in VC syndication networks, however, has its drawbacks. The attention-based view, for example, suggests that with more and more diverse partners, corporate venture capitalists face “limited attention” and ‘bounded rational’ problems. As a result, they increasingly choose to focus their attention on limited issues and on the answers that they want to hear (Ocasio, 1997, 2011). Put another way, corporate venture capitalists cannot spot all the useful elements and cannot consider the entire set of potential opportunities simultaneously, resulting in a decrease of the marginal benefits of syndicating with diverse partners. Inevitably, some novel and valuable knowledge and technology have been neglected, and the efficiency of decision-making becomes lower in this process.

Taken together, the above arguments suggest that CVC units’ degree centrality has a positive latent mechanism, in that more VC partners create more value, and a negative latent mechanism, in that limited attention reduces performance. Together, this yields an inverted U-shaped effect on corporate investors’ innovation performance. Thus, we hypothesize that:

Hypothesis 1. There is an inverted U-shaped relationship between a CVC unit’s degree centrality in its VC syndication network and the corporate investor’s innovation performance.

2.2.2 The quality of the partners

Eigenvector centrality is commonly used to measure the partners’ quality (Hochberg et al., 2007), as its prominence to better-connected partners (Bonacich, 1972). The higher the firm’s eigenvector centrality, the higher its status or its partners’ quality is (Panhke et al., 2015).

CVC units and traditional VCs with high eigenvector values in syndication networks are perceived to be high-quality firms and often have high investment performance (Keil et al., 2010a; Ozmel et al., 2013; Podolny, 2001). High-quality can, therefore, decrease the risk of investment failure, which in turn increases the possibility to assimilate novel knowledge. More high-quality partners should, accordingly, improve the corporate investors’ innovation performance. At the same time, with more reputable partners, CVC units can improve their bargaining power during the negotiations. In this way, high-quality VC partners can lower the corporate investor’s innovation costs. Spending less on one investment frees the corporate investor to spend more on the next, increasing its overall innovation performance.

However, coinvesting with high-quality partners comes at a price. Traditional VCs and CVC units have different objectives which can lead to ‘principal-principal conflicts of interests’ (Chahine et al., 2012, p.180). High eigenvector centrality means traditional VCs are more reputable than CVC units in syndicates. As argued by Kang (2019), investee ventures, in this situation, will exert more effort to comply with the requirements from more reputable ones. This means that they are more likely to focus on maximizing the financial returns to the venture, rather than allocate resources to the development of new products or technology which is detrimental to the innovation performance of corporate investors.

Overall, therefore, we expect that, as CVC units’ eigenvector centrality in VC syndication networks increases, corporate investors will benefit from cheaper, more promising investments, which will enhance the likelihood of developing their innovation performance. Beyond a certain point, however, the CVC units will lose their voice in making decisions, leading to a lower level of innovation performance. As a consequence, we hypothesize that:

Hypothesis 2. There is an inverted U-shaped relationship between a CVC unit’s eigenvector centrality in its VC syndication network and the corporate investor’s innovation performance.

The moderating role of tie strength

Whereas degree and eigenvector centrality of CVC units represents the breadth of the syndication relationships, tie strength can be used to describe the depth of syndication relationships. Tie strength is a measure of the number of times that the CVC unit and their partners coinvest, together, in VC syndication networks, in a given time.

2.2.3 On the number of partners

We contend that tie strength will weaken the relationship described by Hypothesis 1. Following Haans et al. (2016), we describe the effects of tie strength on the positive latent mechanism and negative latent mechanism, which together form the inverted U described by Hypothesis 1.

With regard to the positive mechanism, we argue that when degree centrality increases from a low to medium level, assimilating novel new knowledge and nonredundant information will be weakened as tie strength increases for two reasons. First, once CVC units
and their partners invest in investee ventures together, they will form routines. These will improve communication but will lead to the filtering of novel and fresh knowledge and non-redundant information when CVC units try to search and assimilate from investee ventures (Zheng & Yang, 2015). Second, the more times both CVC units and their partners co-invest in ventures, the more difficult to break the existing syndicate traditions which have been built already. Hence, it decreases the likelihood of searching for novel knowledge, information, and technology, resulting in a diminishing rate of corporate investors’ innovation performance.

As for the negative latent mechanism, we argue that as the level of centrality increases, corporate venture capitalists will increasingly struggle with the amount and diversity of the information brought to them by their partners. As a result, they will choose to focus their attention on more pressing issues (Ocasio, 1997). A high level of degree centrality, therefore, leads to lower corporate investors’ innovation performance. However, as tie strength increases, the CVC unit will increasingly focus on familiarity, which will enhance the transformation and exploitation rate of novel knowledge that it gains from its investee ventures. In other words, tie strength will reduce the negative effects of moving from a medium to a high level of degree centrality, in terms of corporate investors’ innovation performance.

As Haans et al. (2016) claimed that such moderating effect on positive and negative latent mechanisms makes inverted U-shaped curve flat. Therefore, we posit the following hypothesis:

**Hypothesis 3.** Tie strength flattens the inverted U-shaped relationship between degree centrality in VC syndication networks and corporate investors’ innovation performance.

### 2.2.4 On the quality of the partners

We argue, further, that tie strength moderates the inverted U-shaped relationship between eigenvector centrality in VC syndication networks and corporate investors’ innovation performance. We contend that, when eigenvector centrality increases from a low to medium level, tie strength tends to make the best of partners’ reputation and leads to a faster development rate of corporate investors’ innovation performance.

However, when eigenvector centrality in VC syndication networks increases from a medium to the high level, the more syndication relationships between CVC units and traditional VCs, the more likely traditional VCs will lead the investee ventures to maximize their financial benefits and put CVC units under pressure in which they are less likely to chase strategic objectives for corporate investors as much as possible (Hallen et al., 2014; Kang, 2019). As a result, the search process is restricted and the chance of assimilating novel knowledge and technology becomes harder for developing corporate investors’ innovation performance. In line with traditional VCs’ financial objectives, investee ventures prefer to obtain capital gains first for survival. Hence, more reputable traditional VCs can prevent corporate investors from appropriating value leading to the decline of corporate investors’ innovation performance.

Consequently, we expect that tie strength amplifies both the benefits of positive latent mechanism and costs of negative latent mechanism. Thus, we propose our fourth hypothesis:

**Hypothesis 4.** Tie strength flattens the inverted U-shaped relationship between eigenvector centrality in VC syndication networks and corporate investors’ innovation performance.

### 3 | METHODOLOGY

#### 3.1 Empirical setting

We test our hypotheses using data from the pharmaceutical industry. We do so because firms in the pharmaceutical industry routinely make CVC investments (Dushnitsky, 2006), publish patents (Fontana et al., 2013), and produce products that are highly regulated (Dong & Yang, 2016). For this reason, the pharmaceutical industry is commonly used in CVC and innovation management studies (Gilsing et al., 2008; Rothaermel & Deeds, 2004). Following prior research (Dong et al., 2017), we defined the pharmaceutical industry based on the *Standard Industrial Classification (SIC)* code as 2833-2836.

#### 3.2 Data collection

The dataset was built as follows. We collected innovation data from two sources. First, we collected data regarding drug development, using the United States Food and Drug Administration (FDA) Drugs@FDA database. This database describes all approved drugs, since 1985, and includes information such as the approval date, drug name, active ingredients, the company. We collected all the 63,105 records from 2002 to 2016. Then, we gathered all the patent data, for the pharmaceutical industry, from PATSTAT (Autumn, 2019).

We retrieved VC data from the Thomson Reuters Eikon database, which is the most widely used database in VC research and includes every single VC investment since 1961 (Röhm et al., 2020). We excluded all the records with undisclosed VC firms. Doing so led us to identify 23,927 VC investments, involving 241 unique CVC units, 2,408 unique traditional VCs, and 3,145 investee ventures during the period from 1998 to 2016. We adopted a five-year time window to build the syndication networks. Thus, the start year of our dataset is 2002. Figure 1 presents an example of a VC syndication network, focusing on the pharmaceutical industry, during the 5-year time period 2012–2016. The red nodes, in Figure 1, represent the CVC units while the blue nodes represent their partners, namely the traditional VC firms.

Finally, we used the Orbis database, Standard & Poor’s Compustat North America, and Global databases to collect the data for the firm-level control variables described below.
3.3 Key measures

3.3.1 Innovation

Following previous research (Kalcheva et al., 2018), we create a variable that counts the number of FDA-approved new drugs filings for firm $i$ in year $t + 1$, to capture innovation at the firm-year level. We measure innovation in $t + 1$ to avoid reverse-causality. If a firm has no approved FDA filing in a given year, we assign a value of 0. For robustness checking purposes, and given that patent data is a frequently-used measure for innovation performance (Dong et al., 2017), we also estimate the number of patents for firm $i$ in year $t + 1$.

3.3.2 Degree centrality

We use degree centrality to comment on the effect of the number of partners. Following prior work on venture capital centrality (Hochberg et al., 2007), we compute degree centrality as the count of syndication ties a focal VC has in the network (Miura, 2012; Dong et al., 2017). Since we only focus on undirected, weighted network, degree centrality for a particular CVC unit $i$ during the past five years (from year $t - 4$ to year $t$) is:

$$Degree \text{ centrality}_i = \frac{\text{No. of CVC unit's partners}_{t-4,t}}{\text{No. of VC firms}_{t-4,t-1}}$$

3.3.3 Eigenvector centrality

Eigenvector centrality considers the ‘quality’ of the partners (Hochberg et al., 2007). Eigenvector centrality indicates the extent to which the prominence of a focal VC’s partners determines how central the focal VC is (Hochberg et al., 2007; Miura, 2012; Dong et al., 2017). Following prior studies (Bonacich, 1972, 1987), we define the eigenvector centrality of a CVC unit $i$ in a 5-year time window (between $t - 4$ and $t$), as a constant multiply the count of the centrality of its neighbors. We thus have:

$$X_t = \lambda^{-1}\sum A_{it}X_t$$

which can be rewritten as

$$\lambda x = Ax$$

where $A$ is the adjacency matrix of VC syndication networks, $x$ denotes its eigenvector while $\lambda$ is its corresponding eigenvalue (Miura, 2012). The convention is that eigenvector centrality equals the value which is corresponding to the dominant eigenvalue of the adjacency matrix (Cvetkovic, 1995; Miura, 2012), shown by the following formula.

$$\text{Eigenvector centrality}_i = \max(\lambda)$$

3.3.4 Tie strength

Tie strength captures how frequent and close two partners interact with each other in a given time (e.g., Granovetter, 1973; Hansen, 1999; McFadyen et al., 2009). As such, tie strength can be used to describe the depth of the relationship. Using this definition, we counted how many times two VC firms invest together during the past 5 years.

Control variables

We control for several factors known to impact innovation performance. We control for: (1) Patent Stock, which refers to the total number of patents a corporate investor has been granted, with a 15% depreciation rate. It is well established that the past inventive history can impact the current capability for developing innovation (Xu, 2015), thus we incorporate patent stock as a control variable and

Matching the above samples led to the creation of a final sample with 58 corporate investors, headquartered in 15 countries, and 835 firm-year observations in the period of 2002–2016. The unit of analysis in our study is the corporate investor, and all of our sample firms are prominent pharmaceutical firms, that have made CVC investments, in their specialized VC syndication networks, published patents and registered drugs, between 1998 and 2016.
adopt the method which was proposed by Hall (1990); (2) R&D Intensity, calculated as R&D expense divided by total sales, as a measure of the firm’s R&D inputs in innovation (Cohen & Levinthal, 1990; Dong et al., 2017); (3) Firm’s Financial Leverage, which indicates firm’s risk appetite and is calculated as long-term debt divided by total assets (Dong et al., 2017; Greve, 2003); (4) the Age of corporate investors, which is calculated as the total years that corporate investors have been established since their inception because older firms are too rigid to enhance innovation performance (Kelly & Amburgey, 1991); (5) the Size of corporate investors, measured by the natural logarithm of total sales and plus one because larger firms have more resources and thus are better able to develop more new products (Dong et al., 2017); (6) the firms location, using a US dummy, which we set equal to one if the headquarter of a sample firm is in the U.S., and zero otherwise. Finally, we control for year-specific effects using year dummies. Since all of our sample firms are corporate investors in one industry, we do not need to control for industry or investor type.

3.4 Analytical approach

Our dependent variable is a count variable, with nonnegative integer values, for which the mean is not equal to the variance (mean = 18.111, SD = 30.213). Therefore, we test our hypotheses using a negative binomial regression (Hausman et al., 1984). We estimate Equation 5 to test Hypothesis 1 and Hypothesis 3 and Equation 6 to test Hypothesis 2 and Hypothesis 4.

Innovation\(_it\) = \(\beta_0 + \beta_1\)Degree centrality\(_it\) + \(\beta_2\)Degree centrality\(_it^2\) + \(\beta_3\)Degree centrality\(_it\) × Tie strength\(_it\) + \(\beta_4\)Eigenvector centrality\(_it\) + \(\beta_5\)Eigenvector centrality\(_it^2\) + \(\beta_6\)Eigenvector centrality\(_it\) × Tie strength\(_it\) + \(\beta_7\)Controls\(_it\) + \(\epsilon_i\) (5)

Innovation\(_it\) = \(\beta_0 + \beta_1\)Eigenvector centrality\(_it\) + \(\beta_2\)Eigenvector centrality\(_it^2\) + \(\beta_3\)Eigenvector centrality\(_it\) × Tie strength\(_it\) + \(\beta_4\)Eigenvector centrality\(_it^2\) + \(\beta_5\)Eigenvector centrality\(_it\) × Tie strength\(_it\) + \(\beta_6\)Controls\(_it\) + \(\epsilon_i\) (6)

We estimate both Equation 5 and Equation 6 using random-effects, in order to control for unobserved heterogeneity (Wadhwa & Kotha, 2006; Hausman et al., 1984).

4 RESULTS

Table 1 displays the descriptive statistics of all the variables in our sample while Table 2 presents the pairwise correlations between them. Table 2 returns a number of interesting results. For example, it suggests that R&D Intensity is positively related to Innovation, which is defined here as the number of FDA filings. Table 2 reports that Firm Age and the US Dummy are negatively related to Innovation and, interestingly, Financial Leverage and Firm Size are not significantly correlated with the number of FDA filings. Table 2 reports that degree centrality and eigenvector centrality are highly correlated, which is consistent with prior research (Salman & Saives, 2005). This correlation does not affect our results since these two centrality measures are not added to the same estimation models. All other pairwise correlations are below 0.7, which suggests that multicollinearity is not an issue in our models.

4.1 The number and quality of the partners

Table 3 presents results for three negative binomial regressions with random effects. In all cases, the dependent variable is the number of drug filings approved by the FDA. Model 1 is the baseline model in that it only includes control variables. Model 2 adds degree centrality and degree centrality squared to this specification, in order to test Hypothesis 1. The results show that degree centrality has a statistically significant and positive effect on corporate investors’ innovation performance. This suggests that that coinvesting with other partners can lead to more corporate investors’ innovation performance. That said, the coefficient of the quadratic term is negative and significant. This, when coupled with the positive and significant result for the linear term, suggests that there is an inverted U-shaped relationship between degree centrality and corporate investors’ innovation performance. We confirm this by, first, conducting a U test\(^3\) (Lind & Mehlum, 2010) and then, secondly, by inspecting the data range of the turning point. Both steps are needed to confirm an inverted U-shaped relationship (Haans et al., 2016). U test shows that the slope at \(X_{L1}\) is positive and significant (\(p = 7.581, p < 0.05\)) and the slope at \(X_{L2}\) is negative and significant (\(p = 4.222, p < 0.1\)). Besides that, the turning point appears within the data range (0 < 0.172 < 0.267). Thus, Model 2 establishes that there is an inverted U-shaped relationship between degree centrality and innovation, in support of Hypothesis 1.

Table 4 presents results for another three negative binomial regressions with random effects. Again, in all cases, the dependent variable is the number of new drug filings approved by the FDA. Model 1 is the baseline model. Eigenvector centrality is added to

<table>
<thead>
<tr>
<th>TABLE 1 Descriptive statistics</th>
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<tbody>
<tr>
<td>Mean</td>
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<tr>
<td>Innovation</td>
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<tr>
<td>Degree centrality</td>
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<td>Eigenvector centrality</td>
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<tr>
<td>Tie strength</td>
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<td>Patent stock</td>
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<td>R&amp;D intensity</td>
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<td>Financial leverage</td>
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<td>Firm size</td>
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<td>Firm age</td>
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<td>US Dummy</td>
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Model 2 to test Hypothesis 2. The coefficient of the linear term is significant and greater than zero ($\beta_1 = 6.296, p < 0.01$) while the coefficient of the quadratic term is significant and less than zero ($\beta_2 = -23.084, p < 0.05$). This implies that there is an inverted U-shaped relationship between eigenvector centrality and innovation. We confirm this with a U test ($t = 5.07, p < 0.01$). According to the regression equation, the abscissa of the turning point is 0.136, which suggests that the turning point is located well within the data range (0 < 0.136 < 0.220). Therefore, we support Hypothesis 2.

Figures 2 and 3 illustrate the two inverted U-shaped relationships described in Tables 3 and 4. Both illustrations demonstrate a clear positive and negative latent mechanism.

### 4.2 The moderating effect of tie strength

Model 3, on Table 3, reports a full model, which includes all control variables, degree centrality, degree centrality squared, and their interaction terms with tie strength. Model 3, in Table 4, reports a full model in which eigenvector centrality is interacted with tie strength.

The results from Model 3, in Table 3, suggest that tie strength has a statistically significant moderation effect on the relationship between degree centrality and corporate investors’ innovation performance. The coefficient for the squared interaction term between degree centrality and tie strength is positive and significant.

### TABLE 2 Correlation matrix

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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Innovation</td>
<td>0.257***</td>
<td>0.256***</td>
<td>0.971***</td>
<td>0.139***</td>
<td>0.573***</td>
<td>0.605***</td>
<td>0.074*</td>
<td>-0.034</td>
<td>-0.037</td>
<td>0.060</td>
</tr>
<tr>
<td>(2) Degree centrality</td>
<td>0.257***</td>
<td>0.256***</td>
<td>0.971***</td>
<td>0.139***</td>
<td>0.573***</td>
<td>0.605***</td>
<td>0.074*</td>
<td>-0.034</td>
<td>-0.037</td>
<td>0.060</td>
</tr>
<tr>
<td>(3) Eigenvector centrality</td>
<td>0.256***</td>
<td>0.256***</td>
<td>0.971***</td>
<td>0.139***</td>
<td>0.573***</td>
<td>0.605***</td>
<td>0.074*</td>
<td>-0.034</td>
<td>-0.037</td>
<td>0.060</td>
</tr>
<tr>
<td>(4) Tie strength</td>
<td>0.139***</td>
<td>0.139***</td>
<td>0.573***</td>
<td>0.605***</td>
<td>0.074*</td>
<td>-0.034</td>
<td>-0.037</td>
<td>0.060</td>
<td>-0.012</td>
<td></td>
</tr>
<tr>
<td>(5) Patent stock</td>
<td>0.573***</td>
<td>0.573***</td>
<td>0.605***</td>
<td>0.074*</td>
<td>-0.034</td>
<td>-0.037</td>
<td>0.060</td>
<td>-0.012</td>
<td></td>
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</tr>
<tr>
<td>(6) R&amp;D intensity</td>
<td>0.971***</td>
<td>0.971***</td>
<td>0.573***</td>
<td>0.605***</td>
<td>0.074*</td>
<td>-0.034</td>
<td>-0.037</td>
<td>0.060</td>
<td>-0.012</td>
<td></td>
</tr>
<tr>
<td>(7) Financial leverage</td>
<td>0.139***</td>
<td>0.139***</td>
<td>0.573***</td>
<td>0.605***</td>
<td>0.074*</td>
<td>-0.034</td>
<td>-0.037</td>
<td>0.060</td>
<td>-0.012</td>
<td></td>
</tr>
<tr>
<td>(8) Firm size</td>
<td>0.074*</td>
<td>-0.034</td>
<td>-0.037</td>
<td>0.060</td>
<td>-0.012</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>(9) Firm age</td>
<td>-0.034</td>
<td>-0.037</td>
<td>0.060</td>
<td>-0.012</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(10) US Dummy</td>
<td>-0.034</td>
<td>-0.037</td>
<td>0.060</td>
<td>-0.012</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. $n = 835$.

*p < 0.1. **p < 0.05. ***p < 0.01.

### TABLE 3 Random-effects negative binomial regression results

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degree centrality</td>
<td>$7.581^{***}$ (3.452)</td>
<td>$13.592^{***}$ (3.739)</td>
<td>$13.592^{***}$ (3.739)</td>
</tr>
<tr>
<td>Degree centrality$^2$</td>
<td>$-22.084^{***}$ (–2.870)</td>
<td>$-55.567^{***}$ (–3.204)</td>
<td>$-55.567^{***}$ (–3.204)</td>
</tr>
<tr>
<td>Degree centrality × Tie strength</td>
<td>$-6.067^{**}$ (–2.156)</td>
<td>$-6.067^{**}$ (–2.156)</td>
<td>$-6.067^{**}$ (–2.156)</td>
</tr>
<tr>
<td>Degree centrality$^2$ × Tie strength</td>
<td>$33.791^{**}$ (2.194)</td>
<td>$0.091$ (1.073)</td>
<td>$0.091$ (1.073)</td>
</tr>
<tr>
<td>Tie strength</td>
<td>$0.091$ (1.073)</td>
<td>$0.091$ (1.073)</td>
<td>$0.091$ (1.073)</td>
</tr>
<tr>
<td>Patent stock</td>
<td>$0.055$ (0.034)</td>
<td>$-0.099^{**}$ (–2.161)</td>
<td>$-0.099^{**}$ (–2.161)</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>$-0.381^{*}$ (–1.839)</td>
<td>$-0.300^{*}$ (–1.406)</td>
<td>$-0.300^{*}$ (–1.406)</td>
</tr>
<tr>
<td>Financial leverage</td>
<td>$0.300$ (1.135)</td>
<td>$0.535^{*}$ (1.817)</td>
<td>$0.535^{*}$ (1.817)</td>
</tr>
<tr>
<td>Firm size</td>
<td>$0.203^{***}$ (3.759)</td>
<td>$0.193^{***}$ (3.567)</td>
<td>$0.193^{***}$ (3.567)</td>
</tr>
<tr>
<td>Firm age</td>
<td>$-0.015^{***}$ (–5.082)</td>
<td>$-0.013^{***}$ (–3.967)</td>
<td>$-0.013^{***}$ (–3.967)</td>
</tr>
<tr>
<td>US Dummy</td>
<td>$-0.283$ (–1.272)</td>
<td>$0.072$ (0.269)</td>
<td>$0.072$ (0.269)</td>
</tr>
<tr>
<td>Year dummy</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>$1.493^{***}$ (2.623)</td>
<td>$1.318^{***}$ (2.355)</td>
<td>$1.318^{***}$ (2.355)</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>$-1627.821$</td>
<td>$-1622.149$</td>
<td>$-1622.149$</td>
</tr>
<tr>
<td>Chi-sq.</td>
<td>$281.40^{***}$</td>
<td>$308.39^{***}$</td>
<td>$308.39^{***}$</td>
</tr>
</tbody>
</table>

Note. $n = 835$.

*p < 0.1. **p < 0.05. ***p < 0.01.
(β₂ = 33.791, p < 0.05) and the interaction term between degree centrality and tie strength interaction has a negative and significant coefficient (β₃ = −6.067, p < 0.05). This implies that tie strength flattens the inverted U-shaped relationship between degree centrality and innovation (Haans et al., 2016). Figure 4 plots this moderating effect. The dotted line represents the relationship between degree centrality and corporate investors’ innovation performance at high levels of tie strength, whereas the solid line refers to the moderating effect at a low level. Taken together, these results support Hypothesis 3, which suggests that tie strength flattens the curvilinear relationship between degree centrality and corporate investors’ innovation performance.

Model 3, in Table 4, repeats this exercise and considers the moderating effect of tie strength on eigenvector centrality. We find no statistically significant result, which indicates that tie strength does not moderate the relationship between eigenvector centrality and innovation performance. Thus, we do not find any evidence to support Hypothesis 4.

4.3 | Robustness checks

We employ a number of methods to confirm robustness, as shown in Table 5. First of all, Poisson models offer a natural baseline model for...
count variables (Hausman et al., 1984; Henderson & Cockburn, 1996), which has been adopted in prior innovation research (Gilsing et al., 2008). Thus, we rerun our analysis using Poisson regression and report consistent results. Second, we reran our analysis using fixed effects and found that our results still hold. Third, we re-run our analysis uses the number of patents granted for firm \( i \) in year \( t + 1 \), as an alternative dependent, and obtain similar results. Finally, since running regression without control variables can offer useful information to account for the dependent variable's uncontrolled variance (Glaser et al., 2016), we also estimate models without all the control variables, and again return consistent results.

5 | DISCUSSION

5.1 | Key findings

This study finds that there is an inverted U-shaped relationship between the number of VC partners (degree centrality), in the syndication network and its innovation performance. We find the same, when we account for the quality of the partners (eigenvector centrality). We find, furthermore, that the depth of the relationship (tie strength) moderates the first curvilinear relationship (between degree centrality and innovation performance) but find that depth does not significantly
moderate the second one (between eigenvector centrality of CVC units and their corporate investors’ innovation performance). These are novel findings, and they are remarkable for the theoretical and practical insights that they offer.

5.2 | Theoretical implications

We make a number of clear contributions to scholarship and draw insights from multiple fields. Innovation scholars are increasingly considering corporate venturing as a way of sourcing external information and are well versed in the definition of limited attention, but big questions remain regarding how corporate venturing works and why. At the same time, finance scholars have developed a rich literature on the topic of VC syndication networks and CVC but thus far only considered simple linear relationships between network position and financial performance measures. We contribute to both fields, by introducing non-linear relationships and attention-based views into the discussion of VC syndication networks.

Our study enriches the literature on VC syndication networks. To our knowledge, we are the first to consider how tie strength in VC syndication networks affects the relationship between CVC units’ centrality and the innovation performance of corporate investors. We also contribute to the VC literature by making a clear distinction between the quantity and quality of the CVC unit’s relationship with its syndicate partners. We not only explore the different impacts of these mechanisms but we help to identify interorganizational opportunities and challenges that pharmaceutical firms faced in the development process of innovation too.

Finally, this paper also offers additional insights into the general innovation literature. For example, we contribute to current discussions on how to collaborate with external partners for innovation (Wadhwa et al., 2016; West & Bogers, 2014). We add to the literature which acknowledges the importance of CVC programs for securing new-technology inputs beyond their corporate investors’ boundaries (Diestre & Rajagopalan, 2012; Dushnitsky & Shaver, 2009; Van de Vrande, 2013; Wadhwa & Kotha, 2006). Only a few studies consider the impact of CVC on corporate investors’ innovation (Wadhwa et al., 2016). None, to the best of our knowledge, has examined the curvilinear influences of CVC units’ centrality on corporate investors’ innovation. Hence, our study advances the understanding of what corporate investors need to consider, in terms of the quantity, quality, and depth of syndication relationships with their VC partners, when looking to optimize their innovation performance.

5.3 | Managerial implications

This study offers managers a number of practical insights. First, our results suggest that when CVC units choose their partners, they should concern simple things like the number of partners they have. Managers should realize that ‘too much can be as bad as too little’ (Haans et al., 2016). Our findings suggest, in fact, that a modest number of partners can benefit the corporate investor’s innovation performance most. Second, our results suggest that managers should not only focus on quality and prominence when choosing partners. Our results suggest that more medium-quality partners are

### TABLE 5 Robustness Checks

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Poisson</th>
<th>(2) Fixed effects</th>
<th>(3) Alternative DV</th>
<th>(4) Without controls</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degree centrality</td>
<td>10.203***</td>
<td>13.136***</td>
<td>8.083***</td>
<td>12.787***</td>
</tr>
<tr>
<td>Degree centrality^2</td>
<td>-43.656***</td>
<td>-53.864***</td>
<td>-48.161***</td>
<td>-51.567***</td>
</tr>
<tr>
<td>Degree centrality x</td>
<td>-4.471***</td>
<td>-5.809***</td>
<td>-14.029***</td>
<td>-7.812**</td>
</tr>
<tr>
<td>Tie strength</td>
<td>(-3.156)</td>
<td>(-2.045)</td>
<td>(-7.691)</td>
<td>(-2.524)</td>
</tr>
<tr>
<td>Degree centrality^2 x</td>
<td>26.048***</td>
<td>32.511***</td>
<td>57.834***</td>
<td>41.561***</td>
</tr>
</tbody>
</table>

Note: n = 835.

*p < 0.1. **p < 0.05. ***p < 0.01.
better than more high-quality partners, in terms of innovation performance. Third, the manager should pay attention to the frequency of the interactions and the depth of the relationships. We find, on the one hand, that an increased interaction weakens the positive effect of syndicate partner quantity on corporate investors’ innovation performance. On the other hand, however, we find that deeper relationships and more frequent interactions, weaken the negative effects of having too many partners.

5.4 | Limitations and future research

There is no study without its limitations. In this section, we discuss the main limitations of our study and we reflect upon the future research routes that these, in turn, imply.

First, we use a sample of CVC units from firms in the pharmaceutical industry. We do so because firms from this industry provide the necessary data to test our hypotheses. Theoretically, we do not see any reason why there should be any differences between the pharmaceutical industry and, for example, the biotech industry. The constructs that we use, and the mechanism that we describe, should, in principle, be independent of the empirical setting. That said, we do not know that our findings are true of other empirical settings. We call for future research to consider if the mechanisms we uncovered are valid in other empirical settings.

Second, our sample only includes VCs active in the pharmaceutical industry. We do this simply to set boundary conditions on our data. Clearly, however, VCs and CVCs in the same industry will have a high level of knowledge similarity (Ter Wal et al., 2016). It would be interesting to consider our effects in a cross-industry setting. Theoretically, it could easily be argued that the effects we describe vary based on the level of overlap. For example, the CVC might be able to enjoy the benefits of more related VCs, while it might become more quickly conscious of the costs with more unrelated VCs. We hope that future research will investigate the CVC unit, in diverse syndication networks, which makes cross-industry investments.

Third, we consider the effect of the characteristics of the syndication networks in terms of the firm’s products and we confirm them using patents. We do so because these are widely accepted and commonly used performance measures. That said, there are a host of other outcome measures that could have been used. For example, the number of exits, through IPOs, spin-offs, or acquisitions, could be used to describe output. The stability of the syndication itself too could have been used to describe performance. Our analysis ignores these possibilities, and therefore we call on for future research to test our hypotheses using these measures.

Fourth, VC tends to occur in rounds. Research suggests that both the role of syndication changes with the round, as does the level of syndication (Zhang et al., 2021). Given that our focus, in this paper, is on the characteristics of the VC network—as opposed to the characteristics of the VC investment itself—we do not consider the investment round in our analysis. It is conceivable, however, that the investment round matters for the mechanisms that we describe. For example, information asymmetries, between the CVC unit and traditional VCs are highest in the first round, and trust is built across rounds through repeated interaction. The effect might mean that the mechanisms that we uncover become more important as the number of rounds increases. We call for future research to add these details to the conversation, and to test if the relationships we uncovered are stronger or weaker in the different rounds.

Fifth, our approach is quantitative: we combine large data sets to present an empirical perspective on the subject. We hope that future research will conduct the sorts of in-depth interviews which are needed, and which we miss, regarding the process of syndicate collaboration and the way in which knowledge is exchanged through CVC investments.

Finally, we make use of social network theory to consider the effect of the number (degree centrality), quality (eigenvector centrality), and depth (tie strength) of the CVC unit’s relationships, in its syndicated VC network, on the corporate investor’s innovation performance. Social network theory, however, highlights some potentially relevant additional network attributes, such as density, clustering coefficient, and structural holes. We do not describe these in this study, due to space constraints. However, we hope that future research will expand our work, and will add these to the discussion on syndicated VC networks and innovation. Besides, since the investment environment is full of uncertainty, future research can employ the real options view to study whether and how the interaction mechanism between the CVC unit and its partners at different uncertainty levels differs.

6 | CONCLUSION

This paper examines how the CVC unit’s centrality in venture capital (VC) syndication networks impacts corporate investor’s innovation performance. We explore the subject using a panel of 835 firm-year observations from the pharmaceutical industry. We find that there is an inverted U-shaped relationship between the CVC unit’s centrality in its syndication network—which we measure using degree and eigenvector centrality—and the corporate investor’s innovation performance. This means that the number and the quality of partners that the CVC unit invests with matters: more partners and more quality partners help, but too many partners, irrespective of their quality, hurt. We find, furthermore, that the depth of the partnership—which we measure by tie strength—weakens the diminishing benefits of co-investing with many partners. This means that the strength of the CVC unit’s relationships with its partners allows it to have more partners, without the negative consequences of doing so. Interestingly, we find that the depth of the relationship does not affect the costs and benefits of centrality when quality is taken into account. Jointly, our findings illustrate the danger of the ‘more is always better’ principle in terms of VC centrality. Our findings provide both managers and scholars with in-depth insights on how to organize CVC investments for innovation.
ACKNOWLEDGMENTS
We are grateful to Samuele Murtinu for his valuable guidance. Ruling Zhang acknowledges the financial support from the China Scholarship Council (No. 201806630043).

CONFLICT OF INTEREST
There are no conflict of interest to declare.

ENDNOTES
1 If one CVC unit only makes investment independently, it means this is an isolated point in VC syndication networks. Thus, we use zero to stand for its tie strength for all the years.
2 CVC units and their partners may invest in the same investee ventures, or invest in different investee ventures. Here, we only count the total number of their syndication ties.
3 Suppose the data range is \([X_L, X_H]\).

DATA AVAILABILITY STATEMENT
The data used in this research are available on request from the authors.

REFERENCES

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