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What drives CVC investments ?

An Empirical Test of Social Network Theory Predictions

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***Abstract*—Using data on corporate venture capital (CVC) investments by US corporations between 2001 and 2013, we analyze their CVC expenditures based on their positions in syndication networks and their financial resources. The generalized-method-of-moments models used show that these companies' annual CVC expenditures depend on the number of co-financing relationships they have and their cash flows in the previous year, as well as their prior investments. However, their previous centrality in syndication networks is not significant, contrary to social network theory, which stipulates that prior central positions in syndication networks significantly explain the future network positions of corporate venture capitalists.**

***Index Terms*—corporate venture capital, network, financing, syndication**

1. INTRODUCTION

The acceleration of technological change is accompanied by new organizational forms that allow fast adaptation to changing environments (Baldwin and Clark 2000). In particular, the new environment in high-tech markets undermines interests that are traditionally associated with internal R&D. Indeed, on the one hand, R&D investment appears increasingly risky (Kothari et al. 2002). On the other hand, the income horizon from holding patents on innovations has decreased (Cohen et al. 2000). As such, massive investment in internal R&D alone cannot ensure the sustainability of high-tech firms. These firms are also looking outside their internal R&D laboratories for means to ensure their survival. Therefore, the nature of the means employed by high-tech firms' managers to sustainably generate a sufficient level of cash flow to meet the requirements of funding providers has been interrogated (Henderson and Clark 1990; Dougherty and Corse 1995; Dushnitsky 2006).

Among these means, corporate venture capital (CVC), defined as direct minority equity investments made by established companies in privately held entrepreneurial ventures (Gompers and Lerner 2000a), is particularly interesting. Indeed, Brown et al. (2009) attribute 75% of the technology boom of the 1990s to the massive growth in the supply of financing to young innovative companies during this period. Furthermore, Kortum and Lerner (2000) suggest that venture capital (VC), although it represented, on average, less than 3% of firms' R&D expenses in the period from 1983 to 1992, was responsible for 10% of US industrial innovations in this decade. Constrained by their financial resources, industrial firms are minor players in the VC industry, which is dominated by specialized financial institutions (Dushnitsky 2006). This financial imbalance leads the former to syndicate 90% of their CVC investments with the latter (Basu et al. 2011) to acquire diversified information about future marketable innovations. The VC investments' syndication leads to the creation of an investor network, which means that different types of investors are dependent on resources controlled by others and that the pooling of resources can be beneficial to all involved (Weil and Durieux 2000).

However, from the industrial firms' perspective, the current conditions of VC networks' efficiency remain largely unexplored. First, Basu et al. (2011) stress that CVC research is limited and has only recently attracted renewed interest. Second, CVC studies are based on data from the 1990s, which generally constitute more than 70% of the sample's information. As such, most of the results are biased and do not reflect the current situation. Moreover, as the vast majority of industrial firms embedded in VC networks during the 1990s have since withdrawn, pretending that their CVC investments were efficient seems rather difficult. Third, network theory suggests that a central position is the best way to capture information from other network members. As CVC accounts for only 17% of VC investments, this "best strategy" may not be possible for all industrial firms. Therefore, the existence of a second-best strategy for industrial firms is examined. Finally, the literature indicates that venture capitalists (VClists) do not need the industrial firms' financial resources to finance innovative startups. It follows that the nature of the resources made available by industrial firms to other network members is of particular interest. To the best of our knowledge, Keil et al. (2010) are the first to give some answers to this question, and their seminal works deserve to be extended even further. In particular, the two relationships between the amount that firms invest in CVC and their positions in the syndication network, on the one hand, and between the position in syndication networks and the resources of the CVC parent, on the other hand, have to be confirmed because of their methodological approach (their measure of centrality is debatable) and the data used (the 1996–2005 period, when the information technology (IT) bubble was dominant and was characterized by many investors' irrational behavior).

Using a sample of 284 industrial firms that made at least one syndicated CVC investment with VC firms during the 2001–2013 period, this article aims to study the relational strategies employed by industrial firms to capture information from VC networks. This objective leads us to question the nature of the resources that these firms made available to other network members to sustain their positions in the VC network.

Our results first contribute to the CVC literature. To the best of our knowledge, our study is the first to question the relational strategies that industrial firms use to capture information from VC networks. We show that these firms are pursuing a second-best strategy, which highlights the difficulties that they face in operating within VC networks and opens up new ways of understanding the fluctuating amounts of the CVC investments.

Second, our results have practical value, as they suggest that the relationships with VClists satisfy the industrial firms' information needs. These firms are prone to renew their CVC investments year after year, which indicates that this second-best strategy is satisfactory for industrial firms. Moreover, our study shows that the internal R&D expenses complement past relationships, helping the industrial firms deepen their embeddedness in the VC network. Additionally, the internal R&D expenses can act as a substitute for prior network centrality to improve an industrial firm's position in VC networks. Therefore, the informational benefits from embeddedness in VC networks appear to be related to the knowledge that the industrial firms hold about future innovations and that the collaboration between industrial firms and VClists seems to be based on information exchanges about future marketable innovations. The remainder of the paper is organized as follows. Section 2 describes the study's methodology, the dataset and the sample's characteristics. Section 3 presents and explains the empirical results.

3. Methodology and data

3.1. Methodology

To identify the drivers of the syndicated CVC investments we decided to implement the generalized-method-of-moments (GMM) system developed by Blundell and Bond (1998). From an epistemological perspective, this sophisticated auto-regressive model allows us to consider the effect of past investments decisions on future choices with regard to the same variable. Therefore, the GMM system fits well with the analysis of firms' investments decisions in uncertain environments or when they are compelled to adopt a trial-and-error process. First, an autoregressive model allows us to account for any past CVC investments that may influence the current CVC investments decisions and the number of relationships in the VC networks. Second, the first-difference model of moments (Arrelano and Bond 1991) provides general estimators designed for situations with low T values (i.e., few time periods), large N panels (i.e., many individuals), independent variables that are not strictly exogenous (i.e., correlated with past and possibly current realizations of the error), fixed effects, heteroskedasticity and autocorrelation within individuals (Roodman 2007). However, the properties of these estimators are low when variables are highly persistent: in this case, lagged-level variables are weakly correlated with the first-difference equations. Blundell and Bond (1998) then show that, in the case of highly persistent series, the estimators of the GMM system are more appropriate. The validity of the GMM system requires to test (1) the first-order and second-order serial autocorrelation of the residuals using the Arellano and Bond test and (2) the validity of lagged variables that are used as instruments because of the over-identifying restrictions (Hansen test). Moreover, Roodman (2007) indicates that a large collection of instruments, even if individually valid, can be collectively invalid in finite samples because they over-fit endogenous variables. Therefore, we limit the time span for instruments to the two previous years. Finally, we address problem of missing values according to the recommendations of Holtz-Eakin et al. (1998). That is, we create a set of instruments from the second lag of the dependent variable, one for each time period, and we collapse these instruments into one vector to generate a meaningful moment. In the present paper, we reproduced the results of the robust two-step GMM system with a finite-sample correction to the reported standard errors, without which these standard errors tend to be severely downward biased (Windjmeijer 2005)

3.2. Data sources

The data for our analysis come from the Securities Data Corporation (SDC) Venture Economics database, and we have also gathered accounting information on CVC firms from Orbis (BVD).

First, the SDC database is widely used in VC studies (Keil et al. 2010) and allows researchers to identify the industrial firms that have CV subsidiaries. However, the use of this database and the characteristics of the VC market impose geographic, sectorial and temporal limitations. Indeed, on the one hand, Kaplan et al. (2002) conclude that the information provided by the SDC database does not present important skews, and they note that the SDC database focuses on US VC investments in startups that are also domiciled in the US. Consequently, we chose to focus our study on the US industrial firms financing the startups located in the US. On the other hand, VC activity concentrates on industries that present the best technological development opportunities. Thus, 63% of the financing for which we have information relates to IT[1] startups. As calculating network positions requires

[1] Like Hochberg et al. (2007), we defined these sectors using SIC coding: information technologies (357*, 367*, 48 **, 3663)

ample data, we choose to focus our study on the IT industry and select only the industrial firms that finance startups in this industry. Finally, the IT startup financing led to the swelling of a speculative bubble, starting in the second half of the 1990s. The bursting of this bubble in 2001 led to the withdrawal of investors who were attracted by short-term financial profits. This withdrawal resulted in significant changes in investors' relative positions in the VC network. Because of the major decline in the number of CV firms and investments after the bubble burst in 2001, which shook up the VC investor network, we choose to focus our study on the 2001–2013 period.
At the end of this process, we identified 284 industrial firms that made at least one syndicated CVC investment with VC firms during the 2001–2013 period.
Second, we accessed accounting information on our sample firms from the Orbis (Bureau van Dijk) database. Orbis combines information from regulatory bodies, among other sources, and delivers financial and accounting information on approximately 170 million companies worldwide. The OECD used this database to address the need for a firm-level micro-data analysis on this institution (Pinto Ribeiro et al. 2010).

Dependent Variables

Ernst & Young regularly stresses the substantial annual variation in corporate venture investments. Thus, we decided to highlight some determinants of industrial firms' decisions to invest in IT startups before we focused on explaining variables regarding the annual relationships of industrial firms in VC investor networks.
Firm's annual CVC investment: From SDC data, we calculate the annual CVC investment of each industrial firm in our sample for the 2001–2014 period.
Annual number of co-investors: SDC allows us to calculate the number of firms in which each industrial firm invests each year. As the size of the investor network varies each year and, in turn, the possible number of relationships, we standardized this variable.

Independent variables

Our independent variables are the prior annual number of co-investors, prior annual closeness centrality, prior annual cash flow, prior annual R&D expenses and prior annual net sales.
Prior annual number of co-investors: We operationalize the dependent variable lagged by one year. The prior annual number of co-investors allows us to account for each industrial firm's commitment to the syndication in which it is embedded.
Closeness centrality: We used the closeness centrality, which was first proposed by Freeman (1979), to measure path lengths in the network. Closeness centrality is a commonly used measure of centrality (Hansen 2002; Fershtman and Gandal 2011; Aalbers et al. 2013; Iacobucci and Hoeffler 2016). As defined by Freeman (1978), a node's closeness centrality is the sum of its graph-theoretic distances from all other nodes, where the distance from a node to another is defined as the length (in links) of the shortest path between them:

$$Cc(ni) = (g-1)/\sum_{j=1}^{g-1} d(ni,nj)$$

where g is the number of investing firms and $d(n_i, n_j)$ is the geodesies that link firms ni and nj. Summing the distances of all reachable related firms, excluding the focal one (g - 1), provides firm n_i's total closeness score. This measure is standardized, such that a firm has the shortest path length (i.e., is closest) to related firms when the index is one and the longest path length when the index is near zero. As stated by Borgatti (2005), closeness centrality can be interpreted as the index of the inverse time until arrival of the information that flows through the network. In other words, firms with high closeness centrality scores are well positioned to obtain novel information concerning future marketable innovations when they are most valuable. Compared with the eigenvector centrality used by Keil et al. (2010), closeness centrality has two advantages (Bonacich 2007). First, closeness centrality does not require any hypotheses regarding the shape of the network, while eigenvector centrality cannot be used if the network in question contains two or more components that are isomorphic images of one another. As such, the closeness centrality measurement can be undertaken easily, while the eigenvector centrality measurement demands an analysis of network properties. Second, the closeness centrality measurement is less sensitive than the eigenvector centrality measurement to the number of the network relationships. Therefore, the closeness centrality measurement allows us to disentangle the effects of (1) the centrality and (2) the number of relationships on CVC investments, which is one of our study's objectives.
Cash flow: As with all the accounting variables, we obtained net cash flow data from the Orbis database. Cash flow is the net amount of cash and cash equivalents available at the end of each fiscal year. We used cash flow as a proxy for the available resources for corporate venture activities.
Annual R&D expenses: An income statement's R&D expenses reflect the firm's propensity to innovate. Chesbrough (2006) stresses the complementary roles of external and internal innovation in the quest for new technologies and new markets. Therefore, the amount of R&D expenses should influence the amount of CVC investments and the number of relationships in the VC network.
Annual net sales: As stated by Park and Vermeulen (2015), "From a startup's point of view, engaging with a corporate investor can be alluring on many fronts: big companies have established distribution lines, strategic

partners, deep domain intelligence, not to mention an experienced sales force and a global presence. If a startup could access even a sliver of some of these resources, it could make all the difference". Therefore, VC investors have an incentive to invite industrial firms that represent the best access to product markets, and annual net sales are a good proxy for that access.

Control variable

Annual amount of VC investments: Annual National Venture Capital Association (NVCA) reports highlight the volatility of VC investments. Investments increase when good opportunities appear and drop sharply when the technology seems mature. Therefore, we decided to control for the opportunity link to the IT market using the annual amount of VC investments in the IT industry.

4. Empirical Results

Our study first highlights the profile of industrial firms that have been engaged in CVC activities since the IT bubble burst in 2001. Table 1 shows that CVC investments concern young firms with limited CVC experience. The descriptive statistics associated to these firms highlight many interesting points. First, the considerable variation in the annual CVC investment is worth noting. Indeed, the standard deviation associated with this variable is 3 times larger than the variable's mean, and the interquartile range is 3 times larger than the median. Second, the descriptive statistics associate with cash flow and annual net sales highlight the size disparity between our sample firms. The interquartile range associated with these variables is approximately 5 times greater than the median, and the variables' means are higher their median, meaning that the size distribution of our sample is right-skewed. Third, on average, our sample firms maintain 4 relationships with VC investors, but the number of relationships range from 1 to 86. Fourth, the variation in closeness centrality appears more concentrated, but the weak mean and median values indicate that corporate investors are not located at the network's center. Finally, the total annual VC investments in IT appear stable over the study period.

Table 3 points out the drivers of the CVC investments. First, and, all else being equal, industrial firms show a propensity to increase their CVC investments year after year (Model I to Model VI). Therefore CVC investments seem fulfill the objectives that industrial firms assign to them. Second, internal R&D expenses positively and strongly significantly guide CVC investments. Consequently, the latter appears to be an additional means to the former to improve the innovative capabilities of the firm (Model I). Third, the CVC investments are significantly constrained by the firm's cash flow (Model II). This explains why the CVC investments slow down during the 2007 financial crisis. However, Gompers and Lerner (2000b) stress that VClists' investments are primarily constrained by the number of good opportunities. Financial investors are thus able to consistently capture information about marketable innovations, while industrial firms may have limited access to this information because of their financial limitations.

We then compared the merits and limitations of two possible relational strategies for the industrial firms embedded in VC networks (Model III to Model VI).

On the one hand, Model III shows that the prior number of co-investors significantly and positively affects the current amount of CVC investments. However, Model VI highlights the moderating effect of past CVC investments on the relation between prior number of co-investors and the current amount of CVC investments. All in all it appears that the CVC investments aim to maintain relationships with VC investors: the more an industrial firm has initiated relationships with VC investors the more it has to invest year after year. Nonetheless, an industrial firm that has already signaled its capacity to invest large CVC amounts in the past can lower its current CVC investments. Since the investment duration of industrial firm in a start-up is about three years (Hochberg et al. 2007) this result comes as no surprise: industrial firms able to show their capacity to invest punctually large amounts have a superior ability to maintain their co-investors relationships.

On the other hand, the prior closeness centrality of the industrial firms does not influence their current CVC investments (Model IV) while the Model VI does not indicate any effect of the prior CVC investments on the relation between the past closeness centrality of the industrial firm and the amount of its current CVC investments. Therefore it seems very difficult to claim that the search of a central position guides the CVC investments of an industrial firm: First the descriptive statistics indicate that the closeness centrality of our firms sample is low, second we show that the prior closeness centrality of industrial firms do not guide their current CVC investment. Finally, using sophisticated autoregressive model we fail to highlight any relation between the past CVC investments and the prior closeness centrality on the one side and the current CVC investments on the other side.

In sum, the results of the GMM system we have implemented indicate that prior co-investors relationships guide future CVC investments. Contrary to the social network theory' predictions the industrial firms embedded in VC networks do not attempt to reach a central position and their current closeness centrality do not guide their futures CVC investments. Thefore, CVC investments could be considered as relational investments that R&D active industrial firms makes in order to diversify their information sources about future marketable innovations.

5. Conclusion

Using more recent data and a measure of centrality that disentangles the centrality measure from the number of relationships in VC networks, our study's results partially support the claims of Keil et al. On the one hand, we show that industrial firms' unique resources boost their centrality in the VC network, even if those effects appear to be very limited. On the other hand, our study shows that these unique resources also influence the number of relationships that industrial forms have in VC networks. Industrial firms' unique resources are thus seemingly a means of establishing relationships with any VClist, not just the more centrally positioned among them in VC networks. Finally, our study shows that the industrial firms rely on the past number of relationships in the VC network to determine the current amount of CVC investments, while prior centrality has no effect on this decision. In terms of an investment decision highlighting a firm's strategy, the industrial firms in our sample do not appear to attempt to improve their positions in VC networks. They pursue a second-best strategy, i.e., maintaining their current relationships in VC networks. Overall, our results indicate that the VClists certainly consider access to the product market when they invite industrial firms to join syndications. However, it is far from being the primary variable informing their decision.

As with all studies, our research has a number of limitations that should be noted. The two main limitations concern the data and the selected variables. To generate homogeneous results, we only included firms in the IT sector. We also chose a specific measure of centrality, but comparing the results generated with different measures would be interesting. Moreover, to complete this research, future studies might conduct in-depth qualitative inquiries. The paper also opens interesting avenues for future research. For example, what is the impact of complementary resources on corporate investors' centrality, contingent on environmental factors such as the economic cycle? Are the syndication practices and the relationships between VClists and CVClists observed in the US the same as those in other countries?

REFERENCES

Aalbers, R., Dolfsma, W., & Koppius, O. (2013). 'Individual connectedness in innovation networks: on the role of individual motivation', *Research Policy*, 42(3), 624-634.

Arellano, M., and S. Bond (1991). 'Some tests of specification for panel data: Monte-Carlo evidence and an application to employment equations', *Review of Economic Studies*, 58(2), 277–297.

Baldwin, C. Y., and K. B. Clark (2000). *Design rules. Vol 1: The power of modularity*. Cambridge, MA: MIT Press.

Basu, S., C. Phelps, and S. Kotha (2011). 'Towards understanding who makes corporate venture capital investments and why', *Journal of Business Venturing*, 26(2), 153–171.

Blundell, R., and S. Bond (1998). 'Initial conditions and moment restrictions in dynamic panel data models', *Journal of Econometrics*, 87(1), 115–143.

Bonacich, P. (2007). 'Some unique properties of eigenvector centrality', *Social Networks*, 29(4), 555-564.

Borgatti, S. P. (2005). 'Centrality and network flow', *Social Networks*, 27(1), 55-71.

Brown, J.R., S.M. Fazzari, and B.C. Petersen (2009). 'Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom', *Journal of Finance*, 64(1), 151-185.

Chesbrough, H. W. (2006). Open innovation: the New imperative for creating and profiting from technology. Boston: MA.: Harvard Business School Press.

Cohen, W. M., R. Nelson, and J. Walsh (2000). 'Protecting their intellectual assets: Appropriability conditions and why U.S. Manufacturing firms patent (or not)', *National Bureau of Economic Research*, Working Paper 7552.

Dushnitsky, G. (2006). 'Corporate venture capital: Past evidence and future directions', in *Oxford entrepreneurship handbook*. Eds. M. Casson, B. Yeung, A. Basu, and N. Wadeson, New York: Oxford University Press, 387-431.

Fershtman, C., & Gandal, N. (2011). 'Direct and indirect knowledge spillovers: the 'social network' of open-source projects', *RAND Journal of Economics*, 42(1), 70-91.

Freeman, L. C. (1978). 'Centrality in social networks Conceptual clarification', *Social Networks*, 1(3), 215–239.

Gompers, P. A., and J. Lerner (2000a). 'The determinants of corporate venture capital success', in *Concentrated corporate ownership*. Ed. R. Morck. Chicago: University of Chicago Press, 17-50.

Gompers, P., and J. Lerner (2000b). 'Money chasing deals? The impact of fund inflows on private equity valuation', *Journal of Financial Economics*, 55(2), 281-325.

Hansen, M. T. (2002). 'Knowledge networks: explaining effective knowledge sharing in multiunit companies', *Organization Science*, 13(3), 232–248.

Henderson, R. M., and K. B. Clark (1990). 'Architectural innovation: the reconfiguration of existing product technologies and the failure of established firms', *Administrative Science Quaterly*, 35(1), 9-30.

Hochberg, Y. V., A. Ljungqvist, and Y. Lu (2007). 'Whom you know matters: Venture capital networks and investment performance', *Journal of Finance*, 62(1), 251–301.

Holtz-Eakin, D., W. Newey, and H. S. Rosen (1988). 'Estimating vector autoregressions with panel data', *Econometrica*, 56(6), 1371-1395.

Huang, H., and C. Xu (2003). 'Financial syndication and R&D', *Economics Letters*, 80(2), 141-146.

Iacobucci, D., and S. Hoeffler (2016). 'Leveraging social networks to develop radically new products', *Journal of Product Innovation Management*, 33(2), 217-223.

Kaplan, S. N., Sensoy, B. A., & Strömberg, P. (2002). 'How well do venture capital databases reflect actual investments?', *Working paper*, University of Chicago graduate School of Business, September.

Keil, T., M. V. J. Maula, and C. Wilson (2010). 'Unique resources of corporate venture capitalists as a key to entry into rigid venture capital syndication networks', *Entrepreneurship Theory & Practice*, 34(1), 83–103.

Kortum, S., and J. Lerner (2000). 'Assessing the contribution of venture capital to innovation', *RAND Journal of Economics*, 31(4), 674-692.

Kothari, S. P., T. E. Laguerre, and A. J. Leone (2002). 'Capitalization versus expensing: Evidence on the uncertainty of future earnings from current investments in PP&E versus R&D', *Review of Accounting Studies*, 7(4), 355-382.

Lehmann, E. E. (2006). 'Does venture capital syndication spur employment growth and shareholder value? Evidence from German IPO data', *Small Business Economics*, 26(5), 455-464.

Lerner, J. (1994). 'The syndication of venture capital investments', *Financial Management*, 23(3), 6-27.

Manigart, S., K. De Waele, M. Wright, K. Robbie, P. Desbrières, and H. J. Sapienza (2002). 'Determinants of required return in venture capital investments: A five-country study', *Journal of Business Venturing*, 17(4), 291-312.

Maruca, R. F. (1999). 'Can big companies nurture little companies'. *Harvard Business Review*, 16-17.

Maula, M. V. J., and G. C. Murray (2001). 'Corporate venture capital and the creation of US public companies', *Presented at the 20th Annual Conference of the Strategic Management Society*.
Maula, M., E. Autio, and G. Murray (2005). 'Corporate venture capitalists and independent venture capitalists: what do they know, who do they know and should entrepreneurs care?', *Venture Capital*, 7(1), 3-19.
Moran, P. (2005). 'Structural vs. relational embeddedness: Social capital and managerial performance', *Strategic Management Journal*, 26(12), 1129-1151.
Muzyka, D., S. Birley, and B. Leleux (1996). 'Trade-offs in the investment decisions of European venture capitalists', *Journal of Business Venturing*, 11(4), 273-287.
Noyes, E., C. Brush, K. Hatten and L. Smith-Doerr (2014). 'Firm network position and corporate venture capital investment', *Journal of Small Business Management*, 52(4), 713-731.
Park, B., and E. P. M. Vermeulen (2015). **'**Debunking myths in corporate venture capital: What works, what doesn't, and how to make it happen', *Lex Research topics in corporate law & economics Working Paper*, 2015-3.
Pfeffer, J., and G. R. Salancik (1978). *The external control of organizations: A resource dependence perspective*. New York, NY: Harper and Row.
Pinto Ribeiro, S., S. Menghinello, and K. De Backer (2010). 'The OECD ORBIS database: Responding to the need for firm-level micro-data in the OECD', *OECD Statistics*, Working Papers, 2010/1.
Plummer, L. A., and Z. J. Acs (2014). 'Localized competition in the knowledge spillover theory of entrepreneurship', *Journal of Business Venturing*, 29(1), 121-136.
Rajan, R. G., and L. Zingales (1998). 'Power in a theory of the Firm', *Quarterly Journal of Economics*, 113(2), 387-432.
Roodman, D. (2007). 'A Note on the Theme of Too Many Instruments'. Washington, DC: *Center for Global Development, Working Papers* 125..
Sorenson, O., and T. Stuart (2001). 'Syndication networks and the spatial distribution of venture capital investments', *American Journal of Sociology*, 106(6), 1546–1588.
Wang, H., R. J. Wuebker, S. Han, and M. D. Ensley (2012). 'Strategic alliances by venture capital backed firms: An empirical examination', *Small Business Economics*, 38(2), 179-196.
Windmeijer, F. (2005). 'A finite sample correction for the variance of linear efficient two-step GMM estimators', *Journal of Econometrics*, 126(1), 25–51.
Wright, M., and A. Lockett (2003). 'The structure and management of alliances: Syndication in the venture capital industry', *Journal of Management Studies*, 40(8), 2073-2102.

Appendix

Table 1. Industrial VC investor profile

Variables	Median	Mean	S.D.	Q1	Q3	Min	Max
Number of years that firm invested over the 2001–2013 period	2	3.7	3.5	1	5	1	13
Firm seniority (years)	11	17	30.59	6	20	1	135
CV experience (years)	9	10	7.5	4.6	15	0	46
Number of rounds that firm participated over the course of its entire VC experience	11	43	124	4	30	1	1794

Table 2. Descriptive statistics of our study variables

Variables	Median	Mean	S.D.	Q1	Q3	Interquartile range	Min	Max	Number of observations
Annual CVC investments ($k)	11,306	42,844.59	130,977.4	3,596.95	38,327.8	34,730.85	0	1,922,832	1156
Number of co-investors	2	4.52	8.12	1	4	3	1	86	1156
Co-investors (standardized value)	.006	.00	1	-.429	.0013	.4303	-.4341	9.59	1156
Closeness centrality	.146	.137	.044	.132	.159	.027	.0004	.2328	1156
Closeness centrality (standardized value)	.2026	0.00	1	-.119	.504	.6230	-3.11	2.17	1156
Cash flow ($k)	605,470	3,087,421	6,588,454	53,450	3,039,600	2,986,150	-28,900	20,776,000	2050
Annual R&D expenses ($k)	402,000	1,246,128	2,038,568	65,361	1,254,193	1,188,832	0	10,611,000	1439
Annual net sales ($M)	4,562	19,600	35,300	814.371	21,600	20,785.63	0	52,708	2060
Total annual IT VC investments ($M)	549	552	7,699	493	618	125	416	672	2060

Table 3. The effects of network position and R&D, cash flow or net sales on corporate venture capital investments

	Model I SYS-GMM	Model II SYS-GMM	Model III SYS-GMM	Model IV SYS-GMM	Model V SYS-GMM	Model VI SYS-GMM
Prior annual CVC investment$_{(t-1)}$	.3412***	.4282***	.2863***	.3666***	.2559***	.3861***
Prior annual R&D expenses$_{(t-1)}$	.6103***					
Prior annual cash flow$_{(t-1)}$		.3368**				
Prior number of co-investors$_{(t-1)}$			.3078**		.9398***	
Prior closeness centrality$_{(t-1)}$				-0.0563		-.5589
Prior number of co-investors$_{(t-1)}$ x Prior annual VC investment$_{(t-1)}$					-.0528**	
Prior closeness centrality$_{(t-1)}$ x Prior annual VC investment$_{(t-1)}$						.0521
IT total VC investment$_{(t)}$	.3896***	.3277***	.4346***	.3652***	.045	.003
Constant	.004	.002	4.6381*	2.41*	7.4875***	5.73***
Year dummies	Included	Included	Included	Included	Included	Included
Hansen test χ^2(p-value)	.250	.368	.307	.144	.195	.303
Arellano-Bond test for AR(1)	-3.58***	-3.63***	-4.46***	-4.60***	-5.28***	-5.24***
Arellano-Bond test for AR(2)	-0.19	.21	1.41	1.51	1.84	2.09*
Number of instruments	35	35	39	39	53	53
Number of observations	204	280	529	529	669	669
Number of groups	55	71	98	98	153	153

*p < 0.1; **p < 0.05; ***p < 0.01

Table 4. Pairewise correlations

		1	2	3	4	5	7	8	9	10	11	12
1	**annual VC investments**	1										
2	**co-investors number**	0.714 (.0000)	1									
3	**closeness centrality**	.205 (.0000)	.400 (.0000)	1								
4	**cash-flow**	.186 (.0000)	.224 (.0000)	.068 (.1124)	1							
5	**annual R&D expenses**	.285 (.0000)	.332 (.0000)	.088 (.0766)	.653 (.0000)	1						
7	**total annual IT VC investments**	.023 (.4407)	.065 (.0268)	-0.072 (.0143)	.0383 (.1008)	.0124 (.6545)	1					
8	**lagged annual VC investments**	.649 (.0000)	.666 (.0000)	.2548 (.0000)	.186 (.0000)	.2754 (.0000)	.0549 (.0714)	1				
9	**lagged co-investors number**	.71 (.0000)	.8837 (.0000)	.4019 (.0000)	.2302 (.0000)	.3372 (.0000)	.0347 (.2546)	.714 (.0000)	1			
10	**lagged closeness centrality**	.267 (.0000)	.3773 (.0000)	.4662 (.0000)	.0682 (.0941)	.0604 (.2006)	-.0788 (0.0096)	.2055 (.0000)	.4005 (.0000)	1		
11	**lagged cash-flow**	.173 (.0000)	.1947 (.0000)	.0601 (.1894)	.7809 (.0000)	.6661 (.0000)	.0208 (.4022)	.1857 (.0000)	.2238 (.0000)	.0681 (.1124)	1	
12	**lagged R&D expenses**	.282 (.0000)	.3251 (.0000)	.0777 (.1419)	.6371 (.0000)	.9791 (.0000)	.0031 (.9153)	.2851 (.0000)	.3323 (.0000)	.088 (.0766)	.6566 (.0000)	1