Alliance Networks, Corporate Investment, and Firm Valuation

Sangho Lee*

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ABSTRACT

This paper examines the impact of corporate alliances on corporate investment decisions in a network setting. Well-connected firms are centrally located in alliance networks. I hypothesize that more centrally located firms are exposed to greater information flows through the networks and, therefore, possess informational advantages. The informational advantages of central firms allow them to rely less on the information in their stock prices for making investment decisions. Supporting this hypothesis, firms with a higher centrality exhibit lower investment-to-price sensitivity. This finding is robust to a variety of network centrality measures and endogeneity in alliance formations. Notably, the effect of centrality is not the same across alliance types. More integrated forms of alliances including joint ventures, technology transfer, R&D agreements, and manufacturing agreements seem to exert a stronger influence on the investment-to-price sensitivity. In fact, only the centrality based on these alliances shows a positive impact on both market valuations and announcement effects, suggesting that these alliance networks likely convey value-enhancing information. Overall, my results show that alliance networks are conduits of information that impact corporate investment decisions.

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1. Introduction

Firms often collaborate with other firms, universities, and government institutions in a variety of fields (Schilling 2015). Corporate alliances emerge as collaborative organizational structures. In the theory of the firm, alliances take an intermediate point on the market-hierarchy continuum (Williamson 1975), thus providing tighter connections than simple arm's length market transactions (Johnson and Houston 2000) without sacrificing organizational flexibility (Chan et al. 1997). Previous research shows that alliances enhance firm value and performance.[1] One important source of gain is a specialized organizational structure for knowledge transfer (Jensen and Meckling 1992), which creates greater information flows between alliance partners (Gomes-Casseres, Hagedoorn, and Jaffe 2006). I extend this line of research by studying how the improved information environment through alliances affects corporate investment.

To gauge the informational advantages for firms participating in alliances, I consider a network where firms are connected via a variety of alliances such as joint ventures, licensing agreements, manufacturing agreements, marketing agreements, research and development (R&D) agreements, and other forms of strategic alliances. The network of alliances is characterized as a conduit for a broad category of information that can help managerial decisions on corporate investment. For example, firms in alliance networks are exposed to information flows regarding technology-related knowledge, product and/or geographic market prospects, and more general economic conditions. In alliance networks, some firms are better connected than others, and thus have access to a wider range of knowledge resources (Schilling and Phelps 2007). Network analysis captures the degree of connectivity into a concept called "centrality" that indicates the extent to which firms are centrally located in the networks. More centrally located firms in alliance networks are exposed to greater information flows through the networks, and thus possess informational advantages in detecting investment opportunities. In sum, my main research objective is to examine the impact of these informational advantages from alliance networks,

[1] For example, positive stock market reactions are observed for the announcement of joint ventures (McConnell and Nantell 1985; Johnson and Houston 2000) and strategic alliances (Chan et al. 1997). König, Liu, and Zenou (2014) find that R&D alliances increase Tobin's Q. Li, Qiu, and Wang (2016) and Schilling (2015) provide evidence that alliances positively affect patent counts.

proxied by alliance network centrality, on corporate investment decisions. I also identify whether certain types of alliances exert stronger influences than others. Finally, I examine whether these informational advantages from alliance networks indeed enhance firm value.

My main hypothesis predicts that the centrality in alliance networks negatively affects the sensitivity of investment to Tobin's Q, a proxy for the informational content of stock prices. The rationale is that alliance networks provide alternative sources of information that are useful and previously unavailable to managers. Existing evidence shows that corporate investment is largely sensitive to its own stock prices (see Baker, Stein, and Wurgler (2003) for a literature review). Dow and Gorton (1997) point out that an individual firm's stock price not only reflects the value of managerial decisions, but also provides a guidance for managers about the firm's investment opportunities. Specifically, stock market aggregates new information into prices, and managers incorporate the information into investment decisions. Consistent with this idea, Chen, Goldstein, and Jiang (2007) show that the investment-to-price sensitivity increases in the volume of private information in stock prices, because managers can learn information previously unavailable to themselves. Foucault and Frésard (2012) show that cross-listing increases the investment-to-price sensitivity because of the expanded trading venue for informed traders. Chen et al. (2014) and Edmans, Jayaraman, and Schneemeier (2016) show that insider trading regulations attract more outsider trading activities that increase the amount of private information in stock prices, thereby increasing the investment-to-price sensitivity. In a recent theoretical work, Schneemeier (2016) argues that core-firms in a core-periphery network can make more efficient investment decisions because they can extract more information from the financial market. In this paper, an alliance network is characterized as a conduit for valuable information for making investment decisions, generating an informational advantage for central firms in the network vis-à-vis peripheral firms. Thus, I hypothesize that the informational advantage of more centrally located firms in alliance networks may reduce the need for learning from their own stock prices, because they can learn from the information transmitted through the network and incorporate it in investment decisions. In conclusion, I predict that firms with a higher centrality in alliance networks should exhibit lower investment-to-price sensitivity.

To create alliance networks, I use the alliance deals between 1990 and 2013 from Thomson Reuters SDC Platinum Joint Venture and Strategic Alliances database (SDC). An alliance network is the snapshot of all ongoing alliance connections at the end of each calendar year. SDC rarely reports the date of termination for a given alliance, creating a severe data limitation for measuring the ongoing status of alliances. My base specification uses a five-year alliance duration based on the existing literature on R&D alliances (König, Liu, and Zenou 2014; Robinson and Stuart 2007b) and the median value of expected length of alliances available on SDC. Thus, the alliance network in year *t* includes all alliance deals announced in the previous five years (from *t*–4 to *t*). Thus, my alliance networks span the period 1994 to 2013. Alliance networks substantially vary in terms of their size and density as illustrated in Figure 1.

Existing research on network analysis offers several measures of centrality. In this paper, I use the Bonacich measure of centrality (Bonacich 1987), which captures the power and influence of members in networks. This centrality measure is designed to capture the degree of information flows through both direct and indirect connections. More importantly, the Bonacich centrality offers measurement flexibility as to exploit substantial time-series variations in alliance networks. Specifically, parameters are designed to estimate the *absolute* importance of firms in alliance networks, controlling for variations in network size and density. Moreover, this measurement flexibility generates more reliable time-series comparability of centrality, which is desirable for studying the impact of within-firm variations in centrality on the investment-to-price sensitivity.

I first test whether alliance network centrality negatively affects the investment-to-price sensitivity in a regression framework. Specifically, a firm's capital expenditure is regressed on the interaction term between the firm's alliance network centrality and Tobin's Q with a variety of control variables. I find a negative and statistically significant effect of alliance network centrality on the investment-to-price sensitivity. To assess the economic significance of my findings, I compare the investment-to-price sensitivity of central (above sample median) and peripheral firms (below sample median). The estimated investment-to-price sensitivity of central firms (0.641) is 16% lower than that of peripheral firms (0.765). My findings also hold for the centrality measure that only captures the extent of indirect connections, thereby alleviating the concern that

direct connections may affect the investment-to-price sensitivity through other channels than information flows through alliance networks.

Alliance network centrality is the outcome of individual alliance formation, which is likely to be endogenously determined with other corporate policies. To address this concern, I attempt to capture the exogenous part of changes in alliance network centrality, following an approach similar to that used in Anjos and Fracassi (2015). Specifically, changes in alliance network centrality consist of three distinct components: (i) changes in centrality due to heterogeneity in firm characteristics, (ii) changes in centrality due to the initiation of new alliances and/or termination of existing alliances, and (iii) changes in overall network structures. Using firm fixed effects alleviates endogeneity concern (i) above. Regarding (ii), the changes in centrality due to the termination of existing alliances are less problematic. This is because I universally assume that every alliance expires after five years, not relying on the information of firms' endogenous termination decisions. To control for the changes in centrality due to alliance initiation, I define a firm-cohort that consists of all subsequent firm-year observations without forming new alliances. Subsequently, I control for firm-cohort fixed effects by including the set of firm-cohort dummy variables. Using these fixed effects allows controlling for (ii) because any effects of centrality in the firm-year with new alliances will be absorbed by firm-cohort fixed effects. Note that the firm-cohort fixed effects are essentially subsets of the firm fixed effects, meaning that they effectively control for both (i) and the most problematic part of (ii). Thus, any remaining observable effects of centrality are likely to be attributed to centrality changes in centrality due to changes in overall network structures and mostly free from endogenous alliance formation. Under this more restrictive testing environment, I still find a negative and statistically significant impact of centrality on the investment-to-price sensitivity. This result provides evidence that my findings are unlikely to be driven by endogenous decisions of alliance formation.

Even after handling endogeneity issues, still alternative channels exist for explaining my findings without discussing the informational benefit stemming from alliance networks. Thus, I perform additional tests to rule out these alternative explanations. The first test focuses on the mispricing component in stock prices. Baker, Stein, and Wurgler (2003) find that the investment-

to-price sensitivity increases in firms' equity dependence, suggesting that more equity-reliant firms have more incentives to exploit the mispricing in their stock prices. If the stock mispricing is the main driver of my findings, I should observe the stronger impact on the sample of firms depending more on equity financing. However, I find that the effect of alliance network centrality on the investment-to-price sensitivity is weaker and insignificant for low equity-dependent firms. Second, I investigate whether alliance network centrality simply captures for some non-linear relationship between investment and Tobin's Q. For example, if investment is concave in Tobin's Q and firms with a higher centrality are more likely to have high Tobin's Q, then the investment of these firms would be less sensitive to Tobin's Q. My findings still hold for the inclusion of the squared term of Tobin's Q in the regression. Finally, I examine the impact of intangible capital investments, which has experienced a surge along with drastic technology changes since the 1990s (Brown and Petersen 2009). My findings remain qualitatively similar when I include R&D a part of my investment measure.

I further check the robustness of my findings as follows. First, due to limited data on alliances termination, research in alliances networks has had to assume that every alliance discontinues after a specific period of time (Schilling and Phelps 2007). A proper assumption of alliance duration might be crucial to prevent overestimation (assumed duration is too long) or underestimation (assumed duration is too short) of channels for information transmission. My base specification assumes a five-year alliance duration based on the existing literature (König, Liu, and Zenou 2014; Robinson and Stuart 2007b) as well as a small portion of sample alliances reporting their expected alliance length. Hence, I check robustness on the assumption of three- and seven-year alliance durations. Second, I test result robustness by the choice of parameters in the calculation of Bonacich centrality to ensure that the main findings are not driven by my previous choices. Moreover, I run the same tests using two other popular measures of centrality, betweenness and eigenvector centrality. I also conduct robustness tests by excluding sample firms if their total assets change more than 20% in one year, since these firms tend to experience mergers or other material changes in operations. Finally, I use centrality measures based on networks consisting of alliances between U.S. partners to reduce potential concern on any bias from using

global-level alliance networks in analyzing U.S. firms' decisions. All robustness tests indicate that my findings remain qualitatively similar.

After establishing the robustness of the main results, I investigate the cross-sectional implications arising from differences in organizational structure and alliance activities. I have thus far not distinguished between alliances, as any alliance can facilitate information sharing between partners. However, not all alliances are the same, because there is a considerable level of heterogeneity in organizational forms and alliance activities. Existing research shows that knowledge transfer is likely to be greater in more integrative firm boundaries (Stonitsch 2014). Therefore, I test whether more integrative forms of alliances exert a stronger influence on the investment-to-price sensitivity.

I dissect strategic alliances based on the classifications by Villalonga and McGahan (2005). They consider the strength of integration within each choice of firm boundaries, ranging from full acquisitions (most integrative) to divestures (least integrative). Specifically, Villalonga and McGahan (2005) consider four alliance categories: (i) joint ventures, (ii) manufacturing, R&D, and technology transfer, (iii) marketing agreements, and (iv) licensing agreements. The order of the four groups reflects the level of integration, with joint ventures being the highest and licensing agreements being the lowest. In this paper, I merge (i) and (ii), since Villalonga and McGahan (2005) show that the empirical boundary cutoff between the two groups is insignificant. Further, I merge (iii) and (iv) in one group to balance sample size between each classification. Eventually the two groups are *High Alliance*, which includes joint ventures, manufacturing, R&D, and technology transfer agreements; and *Low Alliance*, which includes marketing and licensing agreements. Subsequently, I construct two subnetworks, *High Alliance* and *Low Alliance* networks, and calculate the Bonacich centrality for both. I find weak evidence that the centrality in *High Alliance* networks has a stronger impact on the investment-to-price sensitivity, consistent with the notion that more integrative forms of alliances are more likely to facilitate a greater knowledge transfer between alliance partners.

Finally, I analyze whether alliance networks convey value-enhancing information. I assume that more centrally located firms in alliance networks should have higher valuations if

their informational advantages are value-enhancing, because it will help these firms select better projects. To address this question, I estimate the effect of alliance network centrality on market valuations and alliance announcement effects. The results provide some evidence that only the centrality based on *High Alliance* networks is positively and significantly associated with on market valuations and announcement effects. In sum, *High Alliance* networks are likely to be conduits for value-enhancing information that impact corporate investment decisions.

This paper adds to several strands of the literature. First, to the best of my knowledge, this paper is the first study to examine the implications of corporate alliances on corporate investment policies. Existing studies on alliances examine their determinants of alliances (Bodnaruk, Massa, and Simonov 2013; Li, Qiu, and Wang 2016; Lindsey 2008; Stonitsch 2014; Villalonga and McGahan 2005), announcement effects of alliances (Chan et al. 1997; Johnson and Houston 2000; McConnell and Nantell 1985), changes in operating and innovation performance (Allen and Phillips 2000; Schilling and Phelps 2007), and contractual forms of alliances (Mathews 2006; Robinson 2008; Robinson and Stuart 2007a). This paper adds to the alliance literature by showing that alliances have important consequences for corporate investment decisions.

My findings also highlight corporate alliances as another example of how product market relations affect corporate policies. Originating from the seminal work of Titman (1984), a vast literature provides evidence that both customers and suppliers have profound impacts on corporate policies, including capital structure (Banerjee, Dasgupta, and Kim 2008; Kale and Shahrur 2007; Titman and Wessels 1988; Hennessy and Livdan 2009; Chu 2012), payout policy (Wang 2012), takeover defenses (Johnson, Karpoff, and Yi 2015), and investment decisions (Chu, Tian, and Wang 2015). The literature also documents that industry characteristics and product market competitions are important determinants of capital structure (MacKay and Phillips 2005; Maksimovic and Zechner 1991) and payout policy (Hoberg, Phillips, and Prabhala 2014). However, in contrast to supply chains and industry structures, corporate alliances have received limited attention as corporate policy determinants. My study attempts to fill this gap.

I also add to the recently growing literature on the informational role of stock markets in corporate investment decisions. Managers can learn from the firm's stock prices and use that

information for making investment decisions (Dow and Gorton 1997). Existing evidence suggests that the amount of private information in stock prices (Chen, Goldstein, and Jiang 2007), the intensity of informed trading (Chen et al. 2014; Edmans, Jayaraman, and Schneemeier 2016; Foucault and Frésard 2012), and the stock price of the firm's product-market competitors (Dessaint et al. 2016; Foucault and Fresard 2014) affect the investment-to-price sensitivity. My results complement these findings by suggesting that the flow of information through alliance networks allows managers to rely less on the informational content of stock prices and, thus, reduces the investment-to-price sensitivity.

Finally, this paper contributes to the emerging literature on the application of network analysis in financial economics. Recently, network analysis has been intensively used to model industry-level input-output structures (Ahern 2013; Ahern and Harford 2014; Anjos and Fracassi 2015), firm-level input-output structures (Gao 2015), and product similarities between firms (Hoberg and Phillips 2015). Although alliance networks have been studied in the economics and management literature (Hagedoorn 2002; Rosenkopf and Schilling 2007; Schilling 2015; Schilling and Phelps 2007; König, Liu, and Zenou 2014), this study is the first to build alliance networks to analyze their consequences on corporate policies. I also present a more comprehensive picture of alliance networks by extending the previous literature on alliance networks, which concentrates on R&D collaborations. Finally, this paper illustrates the benefits of the Bonacich centrality in handling substantial time-series variations in network characteristics.

The remainder of this paper proceeds as follows. Section 2 describes the data and variables. Section 3 examines the impact of centrality in alliance networks on the investment-to-price sensitivity. Section 4 analyzes the valuation effects of alliance network centrality. Finally, I conclude the paper with Section 5.

2. Data and variables

2.1. Overview of alliance trends

I obtain alliance data from Thomson Reuters SDC Platinum Joint Venture and Strategic Alliances database (SDC). An advantage of SDC database stems from its wide industry coverage, which is beyond manufacturing and biotechnological sectors where other database (e.g., MERIT-CATI) concentrates their collection (Schilling 2009).[2] Consequently, SDC provides by far the most comprehensive resource of alliance activities, such as joint ventures, research and development agreements, licensing agreements, manufacturing or marketing agreements, and other forms of strategic alliances. These alliance categories are classified by SDC and not mutually exclusive. Since any alliance can facilitate information sharing between partners, I use all types of alliances in this paper. As a result, this paper presents a broader picture of alliance networks than the existing literature focusing R&D alliance networks (König, Liu, and Zenou 2014; Schilling 2015; Schilling and Phelps 2007).

A network of alliance consists of connections originating from the participants of alliance deals. I impose the following selection criteria for the sample of alliance deals. First, a deal must be announced between 1990 and 2013, as SDC started a systematic data collection only in 1990. Second, a deal should not be classified as "rumored" or "intended" since these deals lack any public announcements that can assure an actual establishment of relations. It is worth noting that my study contains not only bilateral alliances but also alliances formed between three or more firms, broadening the existing alliance literature that largely focuses on bilateral alliances (Chan et al. 1997; Johnson and Houston 2000; Stonitsch 2014). Overall, my alliance networks are built on 123,492 alliance deals between 99,623 unique participants.

Panel A of Table 1 summarizes the time-series trend of alliance activities between 1990 and 2013. There was a dramatic surge in alliance activities during the early 1990s. Alliances were

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[2] Due to the lack of mandatory filing requirements, no alliance database is complete in the sense that any database is only able to capture a part of alliance activities existing in the world. Nevertheless, Schilling (2009) shows that the replication of previous studies using different datasets produces qualitatively similar results, suggesting that there is no systematic bias across datasets.

at their peak in 1999 and 2000, but experienced a downturn trend afterwards. The effect of the financial crisis in the late 2000s is remarkable. The total number of announced deals in three years 2009-2011 is even less than those in year 2008. This time-series trend is generally consistent with recent alliance research (König, Liu, and Zenou 2014; Schilling 2015). Regarding the volatility in alliance activities, Schilling (2015) points out that a major technology shock might have unveiled innovation opportunities while it had also increased the uncertainty in economic environment. Specifically, during the early 1990s, technology shocks stimulated a surge in alliance activities as a response to explore new product market opportunities. Once the uncertainty resolved to some extent, alliance demands gradually declined during the 2000s and further dropped after the financial crisis in the late 2000s. In a related perspective, Panel A shows that alliance demands are positively correlated with the number of IPOs. For example, a sharp change in the number of U.S. IPOs coincides with another sharp change in the number of announced alliance deals (e.g. 2000-2001, 2007-2008).[3] Their correlation is 0.46. This finding provides evidence that young, growth firms are important players in alliance.

Panel B of Table 1 reports the time-series trend of alliances by alliance types. These categories are classified by SDC and not mutually exclusive, implying that an alliance deal may involve contractual agreements in multiple aspects. In this paper, I use the following SDC classifications: joint venture, licensing agreements, manufacturing agreements, marketing agreements, R&D agreements, and technology transfer. Joint venture is an organizational form that establishes a separate entity and generally requires parent firms' equity investments. Licensing agreements include licensing and cross-licensing if firms' knowledge assets. Marketing agreements indicate that alliances provide an opportunity to use one firm's distribution networks for the other firms' products and services. R&D agreements generally represent joint projects for development of innovative technologies. Finally, technology transfer indicates whether alliances explicitly target transfers and combination of technological assets of alliance participants. Two caveats need to be mentioned. First, Powell, Koput, and Smith-Doerr (1996) indicate that an alliance can incorporate a much wider range of activities than what alliance announcements

[3] Data is available at Jay R. Ritter's website. I appreciate Jay R. Ritter for making this data publicly available.

suggest, which can blur actual boundaries between alliances types. Moreover, 20-25% of alliances in SDC database are categorized into no specific type. In my main empirical tests, I consider these alliances a part of my sample alliances, because any type of alliances can provide a path for information flows (Schilling and Phelps 2007).

It is worth noting the recent increase in popularity of joint ventures as a choice of alliance types. The proportion of joint ventures surged after the financial crisis in the late 2000s. This finding adds to the existing evidence suggested by Hagedoorn (2002) that shows a decline in joint ventures during the 1990s. I interpret this to mean that in the current economic environment, the benefit of tight firm boundaries offered by joint ventures (Johnson and Houston 2000; Villalonga and McGahan 2005) may outweigh the cost of sacrificing organizational flexibility.

Finally, Panel C of Table 1 reports the correlation matrix between alliance types. For instance, the correlation between joint ventures and licensing agreements measures the likelihood that an alliance is classified into both joint ventures and licensing agreements. Joint ventures are negatively correlated with other alliances except for manufacturing agreements. The positive association between joint ventures and manufacturing agreements suggests that joint ventures are likely to be specialized in formulating new product lineups. On the other hand, licensing agreements and technology transfers are positively correlated, suggesting that a large portion of technology transfer accompanies with licensing of technological assets.

2.2. Construction of alliance networks

SDC rarely reports the date of termination for a given alliance, creating a severe data limitation for measuring the ongoing status of alliances. For example, only 1,699 out of 123,492 deals in my sample report the date of termination. Since it is unlikely that an alliance exists only for the year of formation, existing studies on alliance networks typically assume a specific length of alliance duration for all alliances, generally either a three- (Schilling and Phelps 2007; Schilling 2015) or five-year (König, Liu, and Zenou 2014; Robinson and Stuart 2007b). In addition to follow the literature, I search the contract length information available in SDC. Most alliances involve an open-length contract without any specified length of alliances, but a small fraction of alliances specify the expected length of alliances. Total 4,444 out of 123,492 deals in my alliance networks

report the alliance duration with a mean of 8.72 and the median of 5 years. Hence, I decide to use the five-year duration as my base specification of alliance networks. In Section 3.2., I also assume three- and seven-year alliance durations as a robustness check, and obtain quantitatively and qualitatively similar results.

My base specification uses a five-year alliance duration. As a result, an alliance network in year t includes alliance deals announced in the previous five years (from $t - 4$ to t). I take a snapshot of alliance network at the end of each calendar year. For example, the alliance network in 1998 includes connections stemming from alliance deals announced between 1994 and 1998. Because of this process, my sample period begins in 1994 which is the first calendar year when alliance data is available for the previous five years (1990 – 1994). Eventually, I construct a time-series of alliance networks from 1994 to 2013.

In network analysis, a network consists of nodes (participants) and edges (connections). A standard approach in network analysis represents a network as an adjacency matrix in which each matrix element corresponds to the status of connection between two nodes in the network. More precisely, a network is a $n \times n$ matrix where n is the number of nodes in the network. Then, the (i, j) component of matrix indicates the status of connection between i-th and j-th nodes in the network. Following the literature on alliance networks (König, Liu, and Zenou 2014; Robinson and Stuart 2007b; Schilling and Phelps 2007), I represent an alliance network as an unweighted and undirected adjacency matrix. Unweighted adjacency matrix means that each element of matrix equals 1 if the two corresponding nodes are connected and 0 otherwise. Therefore, all connections have equal values. Next, an undirected network matrix implies a symmetric relationship between nodes. While this symmetry is less realistic, it has an important advantage that all eigenvalues of the matrix are real, which is crucial to compute centrality measures used in the network analysis (Ahern and Harford 2014).

Table 2 summarizes the characteristics of alliance networks between 1994 and 2013. First, Panel A shows that alliance networks follow a very similar time-series trend to the trend of alliance activities shown in Panel A of Table 1, lagging three to five years. For example, Columns (1) and (2) report that the size of networks is at a peak in 2000-2003, while Table 1 shows that the

number of announced deals is at a peak in 1997-2000. Similarly, a sharp decrease of alliance deals in 2008-2009 seems to affect the size of network in 2012-2013. This pattern is unsurprising because alliance networks are built on alliance activities during the previous five years. In fact, the trend in my alliance networks is also comparable to those reported in recent alliance studies (König, Liu, and Zenou 2014; Schilling 2015).

Alliance networks have been gradually decentralized during the sample period. Columns (3) and (4) show that the average degree (i.e., the number of direct connections per participant) has decreased until recently, despite the substantial fluctuation in network size. Consequently, alliance networks become less clustered. Also, there has been a decrease in the average clustering coefficient that measures the extent which a node's neighbors are connected to each other. Finally, Figure 1 helps to visualize the decentralization. For example, despite the similar number of nodes in 1994 and 2010, the figure clearly indicates that nodes have become more scattered, thereby becoming less clustered even in the center of networks.

2.3. Measure of network centrality

Network centrality is my main variable that captures the position of participants in the alliance networks. The idea is that firms with many connections will find their positions in the more central part of networks. Figure 1 illustrates that IBM and Microsoft are linked to many other firms, and in fact located in the central part of networks. In other words, network centrality distinguishes more-connected "central" nodes from less-connected "peripheral" nodes.

In this paper, I use the Bonacich measure of power and centrality (hereafter the "Bonacich centrality") (Bonacich 1987) to measure the influence and information structure embedded in the networks. The Bonacich centrality relies on the notion that a node's importance is determined by how important the node's neighbors. Specifically, the Bonacich centrality not only accounts for the quantity of direct connections but also considers the quality of connections. Specifically, the Bonacich centrality increases not only when I am central but also when my neighbors are more central, because it gauges the importance of indirect connections through neighbors. As a result,

the Bonacich centrality is a famous measure of "influence" in the network analysis (König, Liu, and Zenou 2014; Robinson and Stuart 2007b).[4]

Consider a network consists of n different nodes. The Bonacich centrality $\boldsymbol{C}$ is defined as:

$$\boldsymbol{C} = \alpha(\boldsymbol{I} - \beta\boldsymbol{G})^{-1}\boldsymbol{G}\mathbf{1} \tag{1}$$

where $\boldsymbol{G}$ is an $n\times n$ adjacency matrix, $\boldsymbol{I}$ is an $n\times n$ identity matrix, and $\mathbf{1}$ is an $n\times 1$ vector of ones. For a sufficiently small value of β, $\boldsymbol{C}$ is well defined. α is a scaling factor. β is a decay factor that discounts the effect of indirect connections. It is worth noting that any parametrization of the Bonacich centrality preserves the *ordinal* ranking of centrality within a network, to the extent that β is sufficiently small to ensure well-defined measure.[5] Details of the construction of the Bonacich centrality are provided in Appendix 2.

While the choice of α and β can be arbitrary, existing studies suggest a guideline to the choice of parameters. Following Robinson and Stuart (2007b), I set β equal to three-quarters of the reciprocal of the largest eigenvalue of $\boldsymbol{G}$. In addition, I choose α such that the minimum value of centrality is always equal to unity, which controls for the size of networks.[6] Notice that an isolated single pair of nodes (one node connects to only one other, and vice versa) must be the least connected nodes in any networks. I uniformly assign the minimum value of centrality to nodes in the isolated single pair. Thus, if two participants form an alliance and engage in no other alliances, their centrality values would be fixed at the minimum in the alliance duration. In this context, I design the Bonacich centrality to measure the *absolute* importance of nodes. For instance, the two nodes in my previous example should have no change in their absolute positions, thereby maintaining a constant (minimum) value of the Bonacich centrality.

[4] For robustness check, I run all empirical tests using two other popular measures of centrality, betweenness and eigenvector centrality. The results are very similar.

[5] For robustness check, I run all empirical tests using two other parameter values for β (smaller one and larger one than the original choice of β). Section 3.2 shows that the results remain almost unchanged.

[6] My selection of scaling parameter is different from Robinson and Stuart (2007b) that choose α such that $\boldsymbol{C}'\boldsymbol{C} = n$. This parametrization scales the measure of centrality upward for small networks. For example, the mean centrality in 2013 would be substantially larger than the mean centrality in 2000. Figure 1 shows that this number is less intuitive and inconsistent with the decentralization described in Section 2.1.

Panel B of Table 2 shows the summary of the Bonacich centrality. First, the decreasing mean value centrality is consistent with the decentralization in alliance networks reported in Panel A of Table 2. Interestingly, Panel B shows that the decentralization is more likely attributed to nodes with centrality above median. Specifically, while the median value of centrality decreases by half from 2.07 to 1.00 during the sample period, the 99th percentile of centrality decreases by 78% from 117.71 to 26.30. This result is consistent with the visualization in Figure 1. For instance, even the most central group of nodes in 2013 are less clustered and less connected than those in earlier networks. Based on this consistency between the centrality value and the visual illustration, I conclude that the Bonacich centrality effectively controls for the difference in the size and density of networks.

Panel B also shows that the Bonacich centrality is highly right-skewed, which can distort the estimation results in linear specifications. Following Ahern (2013), I take a log-transformed value of the Bonacich centrality as my main variable of interest in my empirical tests. Specifically, I construct a variable *Centrality* defined by a natural logarithm of the Bonacich centrality. In the population of nodes (i.e. all 547,036 nodes in networks), *Centrality* has a mean of 0.84, a standard deviation of 1.07, and a skewness of 1.55. The minimum value of *Centrality* is fixed at 0 (= log of 1), showing that any two nodes in an isolated single pair are designed to have a fixed minimum value of Bonacich centrality.

It is worth discussing the benefit of using Bonacich centrality in this paper, among other popular network centrality measures in the literature, such as degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality. First, the degree centrality captures the number of direct connections for a given node in a network. Because the degree centrality is unable to measure the effect of indirect connections existing on the network, it fits less to my research objectives that are built on the premise that information can flow through all connections in the alliance networks. Second, the betweenness centrality measures the degree at which a node is well located in terms of shortest paths. Specifically, a node's betweenness centrality is high when the node is located on the shortest paths between many other nodes in a network. Third, the closeness centrality measures the average distance of a given node to all other nodes in the

network. The betweenness and closeness centrality assume that "flows" only occur along the shortest path between two nodes. Yet, Borgatti (2005) points out that information flows are hardly satisfy this assumption, since knowledge transfer can happen in any paths without being limited to the shortest paths. Thus, these centrality measures are less appropriate for my study focusing on the information flows between partners in alliance networks. Finally, the eigenvector centrality is conceptually close to the Bonacich centrality. Both measures gauge the effect of indirect connections and are free from the shortest-path assumption of flows through networks. However, the Bonacich centrality provides greater measurement flexibility with parametrization to account for substantial time-series variations in the size and density of alliance networks (see Table 2 and Figure 1). The eigenvector centrality is arguably an efficient measure when networks are very stable across time. For example, Ahern and Harford (2014) use the eigenvector centrality to evaluate the position of an industry in static input-output networks. In sum, the Bonacich centrality best fits to my research objectives, since the measure effectively captures the degree of information flows through considerably time-varying networks.

2.4. Descriptive statistics

Due to the nature of regional heterogeneity and limited data for foreign corporations, I focus on the sample of U.S. firms to examine the impact of alliance networks on corporate investment policies. My procedure of sample selection generally follows a vast literature on corporate policy. Of all firms in the Compustat/CRSP merged database, I first exclude financial (SIC 6000–6999) and utility (SIC 4900–4999) firms to avoid the strong effect of regulations on these firms. Sample firms should have non-missing values for the following variables: Q, tangibility, cash flow volatility, leverage, cash, capital expenditures, stock return volatility, and the status of paying dividends. I require at least 30 daily return observations to compute annual measures of stock return volatility. My final sample consists of 31,791 firm-year observations in alliance networks between 1994 and 2013. Appendix 1 provides the complete list of variable definition.

As an illustration of key firms, Table 3 lists top 25 central U.S. firms in alliance networks for six different years between 1994 and 2013. I report rankings for selected years with some gap to present distinct changes in key firms, since my alliance networks are largely overlapping in a

short horizon by construction. First, Table 3 identifies several giant firms in alliance networks, such as IBM, Microsoft, HP, GE, GM, and AT&T. It is unsurprising that these firms consistently have been among the most central firms in alliance networks. Table 3 also reports several firms operating in media/entertainment sectors, such as News Corp, Time Warner, and Walt Disney. This result shows that alliance networks in this paper capture alliance activities between participants in a wide range of industries, which extends the existing alliance literature that generally focuses on manufacturing sectors. Now going back to Figure 1, I also indicate the position of key firms reported in Table 3. The figure suggests that even the most central firms contribute to the decentralization observed during the sample period. For example, many key firms were very densely located in 1994, but they became more scattered in 2010 despite the size similarity in two networks.

Table 4 provides descriptive statistics for the variables used in my empirical tests. All but indicator, log-transformed, or bounded variables are winsorized at the 1st and 99th percentiles to prevent the effect of extreme outliers. The sample mean of *Centrality* is 1.57, which is greater than the population mean of *Centrality* of 0.84. This sample mean roughly corresponds to the 75% percentile of the population distribution of *Centrality*. This result is unsurprising since my sample firms are public firms that are likely to have more connections than small and young private firms. Other firm-level characteristics in Panel A are similar to those reported in recent studies such as Leary and Roberts (2014) and Hoberg, Phillips, and Prabhala (2014).

Panel B presents the correlation coefficients table between *Centrality* and other key variables used in my empirical tests. *Centrality* is positively correlated with firm size and age, suggesting that mature firms are more likely to locate centrally in alliance networks. Also, the positive correlation between *Centrality* and Q or R&D indicates that growth, technology-intensive firms are more likely to be central in the networks. It is worth noting that *Centrality* is negatively correlated with leverage but positively correlated with cash, consistent with high-ranked firms in Table 3 operate in high-tech industries characterized by low leverage and high cash holdings.

3. Alliance network centrality and investment-to-price sensitivity

3.1. Main results

My main hypothesis predicts that alliance network centrality decreases the investment-to-price sensitivity. Existing literature shows that managers can learn from the company's stock prices and incorporate that information into investment decisions. In a seminal study, Chen, Goldstein, and Jiang (2007) show that the investment-to-price sensitivity increases in the volume of private information in stock prices, because managers obtain and incorporate new information that is unavailable to themselves. By the same token, if central firms in alliance networks possess informational advantages that reduce the need of additional information for making investment decisions, managers of more central firms in alliance networks may rely less on the information contained in stock prices for making investment decisions. Therefore, I predict that firms with a higher centrality exhibit lower investment-to-price sensitivity.

To test this hypothesis, I estimate the following OLS regression models:

$$I_{i,t} = \alpha_i + \beta_1 \times Centrality_{i,t-1} + \beta_2 \times Q_{i,t-1} + \beta_3 \times Centrality_{i,t-1} \times Q_{i,t-1} + \boldsymbol{\Gamma} \times \boldsymbol{X}_{i,t-1} + \tau_t + \epsilon_{i,t} \quad (2)$$

where $I_{i,t}$ is the capital expenditure (CAPEX) of firm i in year t, $Centrality_{i,t-1}$ is a natural logarithm of the Bonacich centrality of firm i in year $t-1$, $Q_{i,t-1}$ is a proxy for the stock price of firm i measured at year $t-1$, and $\boldsymbol{X}_{i,t-1}$ is a vector of control variables in year $t-1$. The coefficient of interest is β_3 representing the investment-to-price sensitivity of firm i in year t. Also, $I_{i,t}$ is scaled by the beginning value of total assets to maintain consistency in scaling variables.[7] Calendar year (τ_t) and firm fixed effects (α_i) control for any unobservable time- and firm-specific heterogeneity.

I control for cash flows (measured by ROA) because of the well-known effect of cash flows on investments (Fazzari, Hubbard, and Petersen 1988). I also include the interaction term between

[7] Following Chen, Goldstein, and Jiang (2007), I use total assets instead of total capital (typically measured by net property, plant and equipment) to scale variables, because my sample consists of a number of non-manufacturing firms.

Centrality and ROA to isolate the financing channel through which *Centrality* affects investment. Previous literature also suggests that Q is an incomplete, might be even a poor proxy for investment opportunities (Erickson and Whited 2012). Therefore, I use one-year sales growth as a non-price based proxy for investment opportunities (Asker, Farre-Mensa, and Ljungqvist 2015). I control for the interaction term between *Centrality* and sales growth to test whether the impact of *Centrality* on the investment-to-price sensitivity stems from the information content in stock prices or the investment opportunity sets more generally. A positive or insignificant interaction term between *Centrality* and sales growth, which is in the opposite direction of my prediction for the interaction term between *Centrality* and Q, will bolster my argument that alliance network centrality affects the information content in stock prices. I also include firm size (Chen, Goldstein, and Jiang 2007; Foucault and Frésard 2012) as well as cash and leverage (Asker, Farre-Mensa, and Ljungqvist 2015) to control for the firms' investment capacity. For example, large firms or firms with high cash holdings or low leverage may more easily exploit advantages of better investment opportunities.

I had earlier shown that the most central U.S. firms in alliance networks are generally very well-known public firms (Table 3). This finding brings a concern that alliance network centrality merely represents a dearth of private information available to managers rather than the firms' informational advantages, since those prominent public firms tend to operate in environment with significant publicly available information. To address this concern, I additionally include the measure of private information contained in stock prices and their interaction terms with Tobin's Q in the regression, following Chen, Goldstein, and Jiang (2007). Specifically, I use the firm-specific return variation as a proxy for the informativeness of stock prices (Chen, Goldstein, and Jiang 2007; Foucault and Fresard 2014). Following Foucault and Fresard (2014), I calculate the annual measure of firm-specific return variation:

$$Informativeness = \log\left(\frac{1 - R^2}{R^2}\right) \tag{3}$$

where R^2 is the R-squared from the regression of individual stock returns on value-weighted market and industry (SIC 3-digit) portfolio returns. Following Chen, Goldstein, and Jiang (2007),

I use daily returns and require at least 30 observations to compute annual measures of stock price informativeness.

Table 5 reports the estimation results for my main hypothesis. First, Column (1) estimates my baseline regression. The coefficient on *Centrality* × *Q* is negative and statistically significant at the 1% level.[8] This result supports the hypothesis that more centrally located firms in alliance networks have greater informational advantages, and thus rely less on the information contained in stock prices for making investment decisions. It is worth noting that the coefficient on *Centrality* × *ROA* shows no significant impact of centrality on the investment-to-cash flow sensitivity. Furthermore, the coefficient on *Centrality* × *Sales Growth* is positive and statistically significant at the 5% level. This result implies that the investment of more centrally located firms in alliance networks are more sensitive to the investment opportunities measured by sales growth. Thus, it bolsters my argument that alliance network centrality reduces the firms' reliance on information in stock prices, rather than attenuating the firms' responses to investment opportunities.

What is the economic significance of estimated impacts of centrality on the investment-to-price sensitivity? Estimating economic significance is not as straightforward as in simple OLS regression coefficients, since the coefficient of interest is on the interaction term of two continuous variables *Centrality* and Tobin's Q. Thus, I construct an indicator variable that equals 1 if the firm's Bonacich centrality is above my sample median, and 0 otherwise. In other words, this binary version of *Centrality* identifies central (above median) and peripheral (below median) firms. Column (2) reports the estimation results. The estimated coefficient on *Centrality* × *Q* is still negative and statistically significant at the 10% level.[9] For peripheral firms, the estimated investment-to-price sensitivity is 0.765 (β_2: the coefficient on *Q*). For central firms, the estimated

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[8] The estimated coefficient and its statistical significance remains very similar when I replace firm fixed effects with industry fixed effects. This result is actually consistent with the point of Roberts and Whited (2013) that firm fixed effects may generate no material differences in the estimation for first-differenced variables such as corporate investments.

[9] The significance of coefficient becomes weaker, because the binary version of centrality has much less within-firm variations in the time-series. The measure of centrality is sticky by construction as my alliance networks are built on the rollover of alliance deals for five years. Not surprisingly, many firms remain centrally located in alliance networks for consequent years.

investment-to-price sensitivity is 0.641 ($\beta_2 - \beta_3$: 0.765 – 0.124). To sum up, the investment-to-price sensitivity of central firms is 16% (0.641 versus 0.765) lower than that of non-central firms.

Recall that the Bonacich centrality captures the extent of both direct and indirect connections through networks. An interesting question is how the direct and indirect connections affect the investment-to-price sensitivity. Particularly, it is plausible to raise a concern that the direct connections might affect the investment-to-price sensitivity through other channels than information flows through alliance networks. To address this question, I attempt to decompose the Bonacich centrality into two parts, direct and indirect centrality. To begin with, recall that the degree centrality is the number of direct connections per participant. The Bonacich centrality in this paper is scaled to be the sum of all direct connections (each direct connection has the value of 1) and *discounted* indirect connections (each indirect connection has the value of β). Therefore, I can define a measure of centrality purely based on indirect connections by subtracting the degree centrality from the Bonacich centrality, which I call "indirect" centrality. Columns (3) and (4) reports the test results using the degree and indirect centrality. The estimated coefficients on *Centrality* × *Q* are negative and statistically significant at the 1% (degree) or 5% (indirect) level. This result suggests that information flows through indirect connections in alliance networks may also reduce the managerial needs of learning information from their own stock prices.

Finally, I use the probability of informed trading (PIN) as an alternative proxy for the private information contained in stock prices. I obtain the PIN data available in Stephen Brown's website.[10] Details of measures are described in Brown and Hillegeist (2007). Column (5) reports that the coefficient on *Centrality* × *Q* is negative and statistically significant at the 5% level, which provides additional evidence supporting my main hypothesis.

3.2. Identification strategy

The research objective of this paper is to study the impact of centrality in alliance networks on corporate investment policies. There is a severe endogeneity concern since alliance formation is a part of corporate decisions and likely to be endogenously determined with other corporate

[10] I appreciate Stephen Brown for making this data publicly available.

policies. For instance, some latent factors may affect both the extent of alliance connections and investment-to-price sensitivity of firms, creating a negative correlation even under the absence of causal effects. Unfortunately, existing research suggests that it is extremely hard to find a good natural experiment that directly affects the centrality in alliance networks.

In this section, I attempt to capture the exogenous changes in alliance network centrality by following a similar approach used in Anjos and Fracassi (2015). The idea is to control for changes in alliance network centrality that are most likely affected by the endogenous decision of alliance formation. Specifically, changes in alliance network centrality consist of three distinct components: (i) changes in centrality due to heterogeneity in firm characteristics, (ii) changes in centrality due to the initiation of new alliances and/or the termination of existing alliances, and (iii) changes in centrality due to changes in overall network structures. Including firm fixed effects largely reduces the endogeneity concern on (i) to the extent that firm-level heterogeneity is time-invariant. Now, (ii) is most likely affected by firms' endogenous alliance formation decisions. In my empirical setup, changes in centrality due to the termination of existing alliances are less problematic. This is because my alliance networks are built on the assumption that all alliances terminate after five years, regardless of whether they are ongoing or not.[11] In sum, the initiation of alliances is my main identification concern.

To control for changes in centrality due to the initiation of alliances, I define a firm-cohort that consists of all subsequent firm-year observations without forming new alliances. For example, suppose that a firm announces four alliances in 1993, 1996, 1997, and 2001. In 1994, the first firm-cohort "Firm-1994" is constructed using the alliance announced in 1993. "Firm-1994" continues until 1995 as the firm forms no alliances in 1995. However, "Firm-1994" is replaced by a new firm-cohort in 1996, "Firm-1996", since the firm initiates a new alliance in 1996. By the same token, "Firm-1996" exists only one year and is replaced by "Firm-1997" that will continue until 2000 (the last year without forming new alliances). Accordingly, the last firm-cohort should be named "Firm-2001" in this example.

[11] Again, this assumption raises potentially severe measurement problems. Nonetheless, Section 3.2 already shows that my findings are robust to different assumptions on alliance duration.

Using the series of firm-cohort dummy variables for each firm, I control for firm-cohort fixed effects in my regressions. Including firm-cohort dummy variables largely controls for the changes in centrality due to the initiation of alliances. This is because any effects of centrality in firm-year observations with new alliances are absorbed by the firm-cohort fixed effects. It should be noted that the firm-cohort fixed effects control for both (i) above and the most problematic part of (ii) above, since the firm-cohort fixed effects are essentially subsets of the firm fixed effects. In sum, any remaining observable effects of centrality are likely to be attributed to the changes in centrality due to the changes in overall network structure and mostly free from the endogenous alliance formation.

Table 6 reports the estimation results using firm-cohort fixed effects. Columns (1) and (2) estimate the same regression from Columns (1) and (5) of Table 5, except that I replace firm fixed effects with the firm-cohort fixed effects. Still, the coefficient on *Centrality* × *Q* is negative and comparable with the coefficients reported in Table 5. It is worth noting that the significance of coefficients becomes weaker (significant at the 10% level in Column 1 and almost significant in Column 2) than the coefficients from Table 5 (significant at the 1-5% level). This result reflects the fact that using firm-cohort fixed effects enforces more restrictive test environment. Specifically, the number of firm-cohort dummy variables is almost three times larger than the number of firm dummy variables: 15,660 vs. 5,126. Furthermore, any effects of centrality for firms that regularly engage in alliances (on an annual basis or even more frequently) are likely to be absorbed by the firm-cohort fixed effects, thereby reducing the impact of more centrally located firms in alliance networks. In conclusion, my results show that the negative effect of alliance network centrality on investment-to-price sensitivity is less likely to be driven by the endogenous alliance formation.

3.3. Alternative explanations

This section performs additional tests to further support that my main results are likely to be driven by the informational channels of alliance networks, rather than alternative explanations related to stock mispricing, non-linearity in the investment-to-price sensitivity, and investments in intangible capital.

3.3.1. Stock mispricing

This paper is built on the premise that Q proxies for the information in stock price for investment decisions. An alternative explanation may arise from the fact that Q also represents the mispricing in stock market. Baker, Stein, and Wurgler (2003) argue that equity dependent firms' investment is more likely to rely on stock valuations. They find that the investment-to-price sensitivity increases in firms' equity dependence. If my main results are driven by the mispricing component rather than the informational content of stock prices, I should observe that the effect of centrality on the investment-to-price sensitivity is greater for more equity-depending firms. Otherwise, it is more likely that the alliance network centrality interacts with the information content in stock price regarding investment opportunities.

Following Baker, Stein, and Wurgler (2003), I construct subsamples based on the measure of financial constraints that proxy for the firms' equity dependence. Specifically, I use three popular indices of financial constraints: WW Index (Whited and Wu 2006), KZ Index (Lamont, Polk, and Saá-Requejo 2001), and SA Index (Hadlock and Pierce 2010). KZ Index is used in Baker, Stein, and Wurgler (2003). A detail of these indices is described in Appendix 1. Firms are classified into high equity dependence group if their index value is greater than the 66th percentile of the index distribution from my sample firms. Similarly, low equity dependence group include sample firms having index value below the 33rd percentile.

Columns (1)–(6) of Table 7 report the estimation results. Across all measures of equity dependence, the effect of centrality on investment-to-price sensitivity is stronger for low equity-dependent firms. This result rules out the explanation that my main findings are driven by the mispricing component of Q. Rather, the centrality in alliance networks seems to interact with the informational content in Q regarding investment opportunities.

3.3.2. Non-linearity in the investment-to-price sensitivity

Another explanation for the negative impact of alliance network centrality on the investment-to-price sensitivity might stem from the non-linearity in the relationship between investment and Tobin's Q. For example, if investment is concave in Tobin's Q and central firms in alliance networks likely to have high Tobin's Q, then the investment of more central firms in

alliance networks would be less sensitive to Tobin's Q. In fact, the correlation between the log of Bonacich centrality and Tobin's Q is positive (0.09). To address this concern, I include the squared term of Tobin's Q in the regression, following Baker, Stein, and Wurgler (2003) and Chen, Goldstein, and Jiang (2007). Column (7) of Table 7 shows that the coefficient on *Centrality* × *Q* is still negative, though its statistical significance becomes slightly weaker (at the 10% level).

3.3.3. Investments in intangible capital

So far I have focused on the effect of alliance network centrality on the sensitivity of investment in physical assets to stock price. On the other hand, existing literature suggests a rise of investment in intangible capital along with dramatic technology changes since 1990s (Brown and Petersen 2009). Furthermore, alliances are specialized in pooling resources and sharing information to explore risky projects with uncertain outcomes. R&D is a representative example of activities with uncertain outcomes. Hence, it is not surprising that many alliances explicitly or implicitly engage in technology and R&D activities.

I examine how including R&D investment affects my previous findings. I consider a sum of CAPEX and R&D (*CAPEX* + *R&D*). Since many Compustat firms report missing items in R&D expenditure, I only include firms with positive R&D expenditure to ensure that my sample firms represent those who are indeed willing to engage in R&D activities. Column (8) of Table 7 reports a negative and statistically significant. Overall, my findings are consistent with an alternative measure of investment including R&D expenditure.

3.4. Additional robustness

This section tests the robustness of my main results. First, I check whether my main results are robust to the assumption of alliance duration. Section 2.2 discussed that my base specification assumes five-year life for each alliance. Instead, I use three- and seven-year duration of alliances and recalculate alliance network centrality. My sample period is extended to 1992–2013 for three-year duration but restricted to 1996–2013 for seven-year duration, since alliance networks consist of alliance deals announced since 1990. By design, three-year (seven-year) duration networks produce smaller (greater) number of participants per network. Despite differences in sample size,

Columns (1) and (2) of Table 8 show that my findings are robust to different assumptions of alliance duration.

Next, I check the robustness of parameter choices in the calculation of Bonacich centrality. My calculation follows earlier guidelines on the choice of β (Robinson and Stuart 2007b), setting β equal to three-quarters of the reciprocal of the largest eigenvalue of network adjacency matrix $\boldsymbol{G}$. Notice that any parametrization of the Bonacich centrality preserves the ordinal ranking of centrality within a network, to the extent that β is sufficiently small to ensure well-defined value of measures. Hence, I additionally create two Bonacich centrality measures with one higher and one lower β than the one I mainly use in this paper. These measures are named "Bonacich+" and "Bonacich-". Specifically, Bonacich+ (Bonacich-) takes 120% (80%) of the value for β in my main empirical tests. The upper bound is set to 120% such that the Bonacich centrality is well-defined across all networks. Importantly, Columns (3) and (4) of Table 8 show that my finding still holds for the alternative parameter choices in the calculation of Bonacich centrality.

Next, I test the robustness of my main results using two other popular centrality measures: betweenness and eigenvector centrality (See Appendix 2 for a discussion on centrality measures). These measures are log-transformed to mitigate the impact of extreme outliers. To begin with, the betweenness centrality represents how much a node tends to be a gate for information flows through networks. Specifically, the betweenness centrality is high when a node is in the "shortest paths" between many other nodes. Section 2.3 discussed that the betweenness centrality assumes that information can only flow along the shortest paths. Borgatti (2005) points out that information flows are less likely to be the case as knowledge transfer can occur along any paths, not necessarily limited to the shortest path between two nodes. Despite this shortcoming, it is conceivable that nodes with high betweenness centrality are more likely to be exposed to greater information flows through alliance networks, because these nodes are essentially the gate between two distinct parts in the networks. Indeed, Appendix 2 shows that the betweenness centrality is positively correlated (0.6–0.7) with other centrality measures. Not surprisingly, Column (5) reports that my findings remain unchanged after I run the same test using the betweenness centrality. It is worth noting that the statistical significance of coefficient becomes

slightly weaker for the betweenness centrality, suggesting that the measure might underestimate the impact of information flows that can occur outside the shortest paths between participants.

The next measure is the eigenvector centrality, which is defined as:

$$\lambda \boldsymbol{E} = \boldsymbol{G}\boldsymbol{E} \tag{4}$$

where $\boldsymbol{G}$ is an $n\times n$ adjacency matrix, $\boldsymbol{E}$ is an $n\times 1$ eigenvector, and λ is the corresponding eigenvalue. The eigenvector centrality generally takes the principal eigenvector that corresponds to the largest eigenvalue of adjacency matrix $\boldsymbol{G}$. Section 2.3 discussed that the eigenvector centrally is conceptually close to the Bonacich centrality, while the Bonacich centrality provides more measurement flexibility with parametrization for scaling and discount factors.

Recall that I construct the Bonacich centrality to ensure that an isolated single firm pair in any alliance networks must have the same minimum value of centrality (= 1). In other words, the Bonacich centrality in this paper gauges the *absolute* importance of nodes. On the other hand, it can be of interest to look at the effect of *relative* importance of nodes, again controlling for changes in network characteristics. I use the eigenvector centrality to investigate this issue. Specifically, principal eigenvectors are set to have the maximum component equal to unity. In other words, the most important node in each network will have the same maximum value of centrality (= 1). More importantly, the minimum centrality value is likely to increase as networks become smaller. Therefore, the eigenvector centrality in this setting will incorporate the notion that the importance of individual nodes might be greater in smaller networks. Despite differences in the focus of measure, Column (6) shows that my findings still hold for the usage of eigenvector centrality.

I also investigate whether some material changes in firm operations drive my empirical results. To rule out this possibility, I exclude firm-year observations that show annual growth in total assets by more than 20% or less than -20%. These observations may distort the estimation results since they may experience mergers or other material changes in operations. Column (7) shows that my main results hold for the remaining observations.

So far I have worked with global-level alliance networks to examine the effect of alliance network centrality on U.S. firms' investment-to-price sensitivity. This approach has an advantage to capture all alliance activities involving any single U.S. firm. However, there might be a concern that my empirical results may have a bias due to any systematic difference across alliance deals between U.S. firms and others. Thus, I construct alternative alliance networks that consist of alliance deals involving at least two U.S. participants (still not limited to corporations). By design, these U.S. networks are much smaller than global-level networks – they are only about 20–30% in terms of the number of nodes.

Column (8) reports the estimated coefficient using the centrality based on U.S. networks. It is worth noting that the number of firm-year observations only decreases by 18%, suggesting that most of U.S. firms are engaged in alliances with U.S. partners (otherwise the sample size would be much smaller). The coefficient shows little difference from the coefficient estimates using global-level networks. Hence, I continue to rely on global-level networks as they provide more coverage of alliance activities involving U.S. firms.

3.5. More vs. less integrative forms of alliances

This paper so far has presumed that any types of alliances are capable to convey useful information for corporate investment decisions. However, not all alliances are expected to have the same impacts because of a considerable level of heterogeneity in organizational forms and activities across alliances. This section examines this heterogeneity in alliances, focusing on the level of integration within organizations. Existing research shows that knowledge transfer is likely to be greater in more integrative firm boundaries (Stonitsch 2014). Thus, I predict that more integrative form of alliances will have a stronger impact on the investment-to-price sensitivity.

To answer this research question, I divide strategic alliances into subgroups based on the classifications by Villalonga and McGahan (2005). They consider the strength of integration within each choice of firm boundaries, ranging from full acquisitions (most integrative) to divestures (least integrative). Specifically, Villalonga and McGahan (2005) construct four alliance categories: (i) joint ventures, (ii) manufacturing, R&D, and technology transfer, (iii) marketing agreements, and (iv) licensing agreements. The order of four groups are decided by the level of

integration, where joint ventures are the highest and licensing agreements are the lowest. In this paper, I merge (i) and (ii) since Villalonga and McGahan (2005) show that the empirical boundary cutoff between two groups is insignificant. Further, I merge (iii) and (iv) in one group to balance sample size between each classification.

Eventually, I divide sample alliances into two subgroups: *High Alliance* and *Low Alliance*. *High Alliance* includes joint ventures, manufacturing, R&D, and technology transfer agreements.[12] *Low Alliance* includes marketing or licensing agreements. To isolate the effect of individual group, I exclude alliances that belong to both groups. Subsequently, I construct two subnetworks, *High Alliance* and *Low Alliance* networks, and calculate the Bonacich centrality for both. The size of two networks are comparable. *High Alliance* networks produce 15,815 sample firm-year observations, while *Low Alliance* networks produce 12,977 observations. I hypothesize that the centrality in *High Alliance* networks has a stronger effect on the investment-to-price sensitivity.

Table 9 summarizes the estimation results. Columns (1) and (2) separately estimate the effect of centrality in *High Alliance* and *Low Alliance* networks. Column (1) reports a negative and statistically significant coefficient on *Centrality High Alliance* × *Q*, Column (2) reports a negative but insignificant coefficient on *Centrality Low Alliance* × *Q*. In a pooling estimation, Column (3) shows that both coefficients are insignificant, though the coefficient on *Centrality High Alliance* × *Q* is close to be significant at the 10% level. In sum, I find weak evidence that more integrative forms of alliances, including joint ventures, manufacturing, R&D, and technology transfer, tend to be more informative channels for making investment decisions.

[12] In this section, I require that joint ventures should have at least one reported activity for two reasons. First, including all joint ventures substantially increases the size of *High Alliance* group so that they represent the most part of alliance networks. Second, excluding joint ventures without reported activities can eliminate any database issues in omitting alliance activity information. It is also consistent with the sample selection process for strategic alliances, since strategic alliances without reported activities cannot be included in any subgroups.

4. Valuation: do Alliance networks convey value-enhancing information?

4.1. Market valuations

My findings have suggested that central firms in alliance networks possess informational advantages due to their wider access to information available in the networks. An important, and naturally following question is whether these informational advantages are value-enhancing or not. If alliance networks are conduits of value-increasing information, central firms should have higher valuation since their informational advantages will help to select better projects.

To test the value implication of alliance network centrality, I first estimate the following OLS regression models:

$$Q_{i,t+1} = \alpha + \beta \times Centrality_{i,t} + \boldsymbol{\Gamma} \times \boldsymbol{X}_{i,t} + \epsilon_{i,t} + \epsilon_{i,t} \quad (5)$$

where $Q_{i,t+1}$ is Tobin's Q of firm *i* in year *t*+1, $Centrality_{i,t}$ is a natural logarithm of the Bonacich centrality of firm *i* in year *t*, and $\boldsymbol{X}_{i,t}$ is a vector of control variables in year *t*. Following the existing literature on market valuation such as Bebchuk, Cohen, and Ferrell (2009), I control for firm size and age, ROA, R&D, CAPEX, cash leverage, and stock return volatility (proxy for firm risk). Calendar year and firm fixed effects are included in the estimation. My hypothesis predicts that the coefficient on *Centrality* (= β) is positive and significant.

Table 10 reports the results. The first two columns estimate the impact of *Centrality* on Tobin's Q, controlling for the firm fixed effects (Column 1) or firm-cohort fixed effects (Column 2). While both columns report a positive coefficient on *Centrality*, their statistical significance is weak. Thus, I further examine the impact of centrality in two subnetworks, *High Alliance* and *Low Alliance*, as Section 3.5 provides some evidence that *High Alliance* networks seem to exert a stronger influence on the investment-to-price sensitivity than *Low Alliance* networks. Columns (3)-(5) of Table 10 report the estimation results. *High Alliance* network centrality is positively and significantly associated with Tobin's Q (Column 3) while *Low Alliance* network centrality reports no significant relation with Tobin's Q (Columns 4 and 5). To sum up, Table 10 provides some evidence that *High Alliance* networks are more likely to convey value-enhancing information for making investment decisions.

4.2. Announcement effects

A key advantage of SDC database stems from the record of alliance announcement dates, which enables researchers to conduct an event study to look at the wealth effects of alliances. Event study provides an alternative test environment for valuations with less endogeneity concerns. Furthermore, event study offers a unique opportunity that I can test not only the effect of firms' own centrality but also the effect of centrality of *partner* firms. If central firms have greater information resources, the benefit would be greater for firms partnering with more central firms. Hence, I can also look test whether higher centrality of *partner* firms creates more value to the firm forming a new alliance.

It is worth noting that the effect of centrality on CAR might not be as straightforward as in market value regressions. This is because central firms tend to already maintain many existing alliances, implying that their marginal benefit of one additional alliance is likely to be smaller. Thus, the effect of centrality on CAR becomes an empirical question as the smaller marginal benefit of forming alliances may offset the better projection selection ability stemming from more central position in alliance networks.

In this section, I perform an event study on the large sample of alliance announcements between two U.S. public firms. I restrict the sample between two U.S. public firms for two reasons. First, it is feasible to control for firm-level characteristics that affect the announcement effects. More importantly, the identification of *partner* effect is easier since there is a unique partner. I use the sample of 4,122 alliance announcements (8,244 firm-level observations) between 1994 and 2013 with non-missing alliance network centrality in the previous year of forming new alliances. I estimate the cumulative abnormal returns (CAR) in a three-day window (-1, 1), using market-adjusted returns based on the CRSP value-weighted index.[13] Table 11 reports the summary statistics on the announcement effects. Consistent with the existing alliances literature (Chan et al. 1997; Johnson and Houston 2000; McConnell and Nantell 1985), stock market positively reacts

[13] As a robustness check, I also use a two-day window (-1, 0) as well as market models in which parameters are estimated within the window (-239,6). Results remain qualitatively similar (unreported).

to the announcement of alliances on average. The mean value of three-day CAR is 1.194% and 0.188%, while the mean value of dollar wealth gain is $18.84M.

Specifically, I estimate the following OLS regression models:

$$CAR_{i,t} = \alpha + \beta \times Centrality_{i,t-1} + \delta \times Partner\ Centrality_{i,t-1} + \boldsymbol{\Gamma} \times \boldsymbol{X}_{i,t-1} + \epsilon_{i,t} + \epsilon_{i,t} \qquad (6)$$

where $CAR_{i,t}$ is the cumulative abnormal returns for firm i in year t, $Centrality_{i,t-1}$ is a natural logarithm of the Bonacich centrality of firm i in year t-1, and $\boldsymbol{X}_{i,t-1}$ is a vector of control variables in year t–1. I control for the following set of variables: *High Alliance* and *Low Alliance* (Section 3.5), *Horizontal* (an indicator variable of alliances within the same SIC 3-digit industry), and firm characteristics such as size, age, ROA, and R&D. These firm-level controls follow Stonitsch (2014). Finally, I include the same set of characteristics of partner firms in the regression, because wealth effects for alliance announcements can be affected by the characteristics of both firms.

Table 12 shows the effect of alliance network centrality on three-day CAR around alliance announcements. Column (1) shows that *Centrality* has no significant relation with the CAR. This result may imply that previously suggested two economic forces of centrality offset each other. Yet, this finding is also consistent with the full-sample result of market value regressions reported in Table 10 where I find no significant impacts of alliance network centrality on Tobin's Q. Thus, I also estimate the impact of centrality in my two subnetworks: *High Alliance* and *Low Alliance*. Columns (2)–(4) show that only *Centrality High Alliance* positively affects the wealth effects of alliance announcement. These results provide further evidence that *High Alliance* networks are more likely to be conduits of value-enhancing information.

Table 12 also reports the impact of *partner* alliance network centrality on the CAR. Remarkably, *Partner Centrality* is positively and significantly associated with the CAR in three out of four specifications (Columns 1, 2, and 4), controlling for several partner firm characteristics including partner size and age. In Column 3, *Partner Centrality* in *Low Alliance* networks is still positively but insignificantly associated with the CAR. Overall, this finding supports the idea that a firm can experience greater benefits from forming alliances with more centrally located firms in

alliance networks, since these connections can provide a greater exposure to information flows through the networks.

In a seminal study, Chan et al. (1997) find no evidence on the systematic differences in announcement effects across alliance activities, while they show that horizontal alliances (within the same SIC 3-digit industry) are associated with higher market reactions than non-horizontal alliances. I revisit their findings using my large sample of alliance announcements. Table 11 shows that the mean value of CAR is substantially greater for horizontal alliances, consistent with their findings. However, Table 12 shows positive but insignificant coefficients on *Horizontal* in all specifications, suggesting that a greater announcement effects for horizontal alliances might be influenced by both the firm and its partner firm characteristics.

In conclusion, my event study provides some evidence that alliance networks convey value-enhancing information. Central firms in *High Alliance* networks seem to possess greater informational advantages that help choosing better projects that eventually increases firm value. Furthermore, forming alliances with more centrally located firms in alliance networks brings more value to the firm due to a better access to informational resources through alliance networks.

5. Conclusion

This paper performs a large-scale network analysis to study the impact of corporate alliances on corporate investment decisions and valuations. Corporate alliances emerge as collaborative organizational structures. One important benefit of alliances is this organizational structure specialized in knowledge transfer, which creates greater information flows between alliance partners. I characterize a network of alliances as a conduit of useful and publicly unavailable information for making investment decisions. Drawing upon the literature on network analysis, I construct a measure of "centrality" that captures the degree of connectedness for firms in the networks. Specifically, firm with more connections tend to be more centrally located in the networks (higher centrality), thereby having access to a wider range of information resources.

I predict that the centrality in alliance networks negatively affects the sensitivity of investment to Tobin's Q, a proxy for the informational content of stock prices. If alliance networks are conduits of new and useful information for making investment decisions, the informational advantages of central firms in alliance networks may reduce the managerial needs of learning from their own stock prices. Supporting this prediction, firms with a higher centrality exhibit lower investment-to-price sensitivity. In terms of economic significance, the investment-to-price sensitivity of central firms (above sample median) is 16% lower than that of peripheral firms (below sample median). I show that my findings are less likely to be driven by endogenous decision of alliance formation, other alternative explanations, and the choice of network centrality measures. I also find some evidence that more integrative forms of alliances including joint ventures and technology, R&D, and manufacturing agreements exhibit a stronger impact on the investment-to-price sensitivity. Finally, I show that only the centrality in the networks of better integrated alliances is positively related with both market valuations and announcement effects. In sum, my results suggest that alliance networks are conduits of value-enhancing information that impact corporate investment decisions.

This paper contributes to the finance literature in four ways. First, my study is the first to examine the implications of corporate alliances on corporate investment policies. Second, this paper highlights corporate alliances as another example of how product markets affect corporate policies. Alliances have received limited attention as corporate policy determinants despite their unique organizational characteristics. My study attempts to fill this gap. Third, I add to the recently growing literature on the informational role of stock markets in corporate investment decisions. My study adds to the literature by showing that informational flows through alliance networks allow managers to rely less on the information contained in stock prices, thereby decreasing the investment-to-price sensitivity. Finally, this paper contributes to the emerging literature on the application of network analysis in financial economics. Although alliance networks have been studied in the economics and management literature, my study is the first to build alliance networks to analyze their consequences on corporate policies. I also highlight the benefit of using Bonacich centrality for handling substantial time-series variations in network characteristics.

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Table 1

Alliance Deal Characteristics

This table summarizes the characteristics of 123,492 alliance deals announced between 1990 and 2013. An alliance deal includes at least two participants. Panel A presents the number of announced deals, the number of all participants, the number of U.S. participants, the number of U.S. initial public offerings (IPOs: from Jay R. Ritter's website), and the number of U.S. firms in the Compustat/CRSP merged database. Panel B shows the number and proportion of alliance types. Panel C shows the correlation between alliance types. Alliance types are based on SDC classifications and not mutually exclusive (i.e., total may exceed or be less than 100%).

Panel A: Alliance Trends

Year	Deals Announced	All Participants	U.S. Participants	U.S. IPOs	U.S. Firms in Compustat/CRSP
	(1)	(2)	(3)	(4)	(5)
1990	3,030	3,574	1,663	110	5,834
1991	5,321	5,972	2,562	286	5,986
1992	5,451	6,245	2,617	412	6,313
1993	6,090	7,441	2,810	509	7,013
1994	7,204	8,845	3,419	403	7,357
1995	7,716	9,866	3,561	461	7,472
1996	4,710	6,440	2,498	677	7,898
1997	6,212	8,131	3,258	474	7,870
1998	7,192	9,495	3,761	281	7,486
1999	8,188	10,220	4,295	477	7,242
2000	9,851	11,754	4,430	381	6,909
2001	6,357	8,494	2,969	79	6,258
2002	4,630	6,721	2,512	66	5,886
2003	4,705	6,739	3,368	63	5,643
2004	3,929	5,888	3,016	173	5,622
2005	4,653	7,079	3,452	159	5,558
2006	4,581	7,002	3,403	157	5,465
2007	5,333	8,082	3,230	159	5,369
2008	5,114	7,888	2,632	21	5,055
2009	2,190	3,634	1,006	41	4,781
2010	1,360	2,313	582	91	4,620
2011	2,881	4,547	1,127	81	4,534
2012	3,703	5,986	2,066	93	4,462
2013	3,091	5,064	1,537	157	4,522
Total	5,146	6,976	2,741	242	6,048

Panel B: Alliance Types							
Year	# of Deals Announced	Joint Venture (%)	Licensing Agreement (%)	Manufacturing Agreement (%)	Marketing Agreement (%)	R&D Agreement (%)	Technology Transfer (%)
1990	3,030	51.25	14.59	21.68	27.95	12.05	13.43
1991	5,321	48.36	12.35	24.60	32.91	15.24	11.45
1992	5,451	30.32	13.80	21.26	44.29	28.85	11.65
1993	6,090	41.07	14.15	28.75	42.00	24.63	17.06
1994	7,204	50.81	16.30	29.25	35.83	23.65	15.12
1995	7,716	60.77	17.61	30.39	30.30	17.03	13.82
1996	4,710	54.03	18.54	25.46	25.03	13.52	11.46
1997	6,212	49.48	17.53	21.23	19.14	14.15	8.68
1998	7,192	36.51	17.03	20.49	16.24	6.92	5.94
1999	8,188	33.52	11.72	17.04	12.13	4.75	3.44
2000	9,851	31.76	3.74	9.60	11.06	5.62	1.67
2001	6,357	31.05	4.29	12.79	13.78	7.85	0.94
2002	4,630	33.30	4.88	17.28	17.17	9.74	1.81
2003	4,705	17.87	9.56	11.94	21.83	9.22	1.72
2004	3,929	19.34	10.05	12.45	21.79	10.21	2.60
2005	4,653	25.34	8.77	13.88	19.62	9.97	14.49
2006	4,581	28.44	6.51	15.76	16.83	8.88	24.03
2007	5,333	37.63	6.39	17.42	13.78	8.34	15.54
2008	5,114	36.29	3.52	17.32	9.87	7.94	11.58
2009	2,190	56.53	0.50	14.06	4.02	5.48	2.37
2010	1,360	72.79	2.13	18.01	3.24	5.81	1.25
2011	2,881	70.70	1.91	22.25	3.47	7.84	2.12
2012	3,703	57.79	1.30	18.50	3.54	8.91	9.59
2013	3,091	57.78	2.46	16.18	5.08	8.83	3.89
Total	5,146	43.03	9.15	18.79	19.07	11.48	8.85

Panel C: Correlation Matrix of Alliance Types						
Number of Observations: 123,492						
	Joint Venture	Licensing Agreement	Manufacturing Agreement	Marketing Agreement	R&D Agreement	Technology Transfer
Joint Venture	1					
Licensing	-0.2554	1				
Manufacturing	0.2668	-0.0165	1			
Marketing	-0.1503	0.0729	0.0136	1		
R&D	-0.1671	0.0729	-0.0325	0.0654	1	
Tech. Transfer	-0.2034	0.4041	-0.0218	0.0312	0.0775	1

Table 2

Network Characteristics

Panel A shows network statistics for alliance networks between 1994 and 2013. An alliance network is a snapshot of all ongoing alliances measured at the end of each calendar year, based on the assumption that each alliance exists for five years after the announcement of alliances. *Nodes* indicate the number of participants in the networks. *Edges* indicate the total number of pairwise connections between participants in the networks. *Degree* is the number of direct connections per node. For a given node, *Clustering Coefficient* is the ratio of existing connections to all possible connections between directly connected nodes. Panel B provides the summary statistics for the Bonacich centrality. See Appendix 2 for details on the definition and construction of the Bonacich Centrality.

Panel A: Network Statistics				
Year	Nodes	Edges	Average Degree	Average Clustering Coefficient
1994	22,373	36,549	3.267	0.463
1995	26,854	43,459	3.237	0.473
1996	27,210	42,923	3.155	0.473
1997	28,737	44,657	3.108	0.478
1998	30,634	45,581	2.976	0.468
1999	32,068	45,683	2.849	0.440
2000	34,030	49,700	2.921	0.427
2001	35,733	51,363	2.875	0.416
2002	34,982	48,710	2.785	0.403
2003	33,195	44,712	2.841	0.391
2004	30,149	38,754	2.571	0.365
2005	26,432	29,026	2.196	0.320
2006	25,240	25,837	2.047	0.285
2007	26,260	25,991	1.980	0.263
2008	27,354	26,466	2.118	0.277
2009	25,914	24,722	1.908	0.288
2010	22,670	21,074	1.859	0.294
2011	20,933	19,371	1.851	0.320
2012	19,362	18,054	1.865	0.370
2013	16,906	15,877	1.878	0.401
Total	27,352	34,925	2.514	0.381

Panel B: Centrality Statistics								
Year	Nodes	Mean	Std.	Min	Median	99th	Max	Skewness
1994	22,373	9.50	35.82	1.00	2.07	117.71	1,535.19	15.40
1995	26,854	9.27	35.69	1.00	2.07	114.71	1,626.00	16.56
1996	27,210	8.93	34.14	1.00	2.05	106.98	1,587.14	17.18
1997	28,737	8.57	32.63	1.00	2.05	100.76	1,470.26	17.16
1998	30,634	7.91	30.52	1.00	2.04	91.83	1,302.98	17.30
1999	32,068	7.48	29.07	1.00	2.01	89.93	1,358.34	18.27
2000	34,030	7.82	32.44	1.00	1.97	101.79	1,415.29	18.62
2001	35,733	7.61	32.03	1.00	1.79	101.49	1,453.53	19.07
2002	34,982	7.15	30.32	1.00	1.58	93.98	1,360.35	19.15
2003	33,195	6.70	28.28	1.00	1.43	87.17	1,233.84	19.16
2004	30,149	6.04	24.71	1.00	1.32	78.45	985.30	19.08
2005	26,432	4.67	16.38	1.00	1.24	53.92	704.62	18.73
2006	25,240	3.91	12.45	1.00	1.22	41.43	631.61	19.39
2007	26,260	3.66	10.68	1.00	1.22	37.94	673.55	20.98
2008	27,354	3.47	9.82	1.00	1.20	35.02	620.55	20.50
2009	25,914	3.40	9.49	1.00	1.19	32.60	543.14	18.98
2010	22,670	3.39	9.18	1.00	1.16	34.87	413.66	15.31
2011	20,933	3.37	9.24	1.00	1.13	33.78	337.41	14.33
2012	19,362	2.82	6.66	1.00	1.09	26.33	209.36	12.02
2013	16,906	2.84	6.48	1.00	1.10	26.30	224.50	11.85
Total	27,352	6.17	25.56	1.00	1.49	74.66	1,626.00	21.23

Table 3

Top 25 Most Central U.S. Firms in Alliance Networks Between 1994 and 2013

This table lists top 25 centrality ranking of U.S. firms in alliance networks for selected years.

Rank\Year	1994	1998	2002	2006	2010	2013
1	IBM	IBM	IBM	Microsoft	Microsoft	GE
2	AT&T	Microsoft	Microsoft	IBM	GE	Microsoft
3	HP	AT&T	HP	Intel	IBM	IBM
4	Motorola	HP	GE	Sun Microsystems	Intel	Exxon Mobil
5	Digital Equipment	Motorola	Oracle	Motorola	HP	Boeing
6	GM	GM	Sun Microsystems	GE	News Corp	Chevron
7	GE	America Online	Cisco	Cisco	Oracle	Pfizer
8	Apple	Sun Microsystems	AT&T	HP	Time Warner	United Technologies
9	Novell	Intel	Intel	Oracle	Google	Comcast
10	Sun Microsystems	GE	Lucent	EMC	Motorola	Dow Chemical
11	Texas Instruments	Oracle	Motorola	Sprint Nextel	EMC	Intel
12	DuPont	Apple	GM	Walt Disney	Chevron	Merck & Co
13	Intel	Compaq	Yahoo!	Texas Instruments	Cisco	EMC
14	Compaq	Novell	Elec. Data Sys.	Time Warner	Qualcomm	Chespeake Energy
15	Tandem Computers	Unisys	Ford	Comcast	AT&T	Apache Corp
16	Oracle	Texas Instruments	3Com	Yahoo!	Dell	Honeywell
17	Silicon Graphics	Cisco	Commerce One	News Corp	Comcast	PepsiCo
18	BellSouth	Bell Atlantic	AOL Time Warner	Novell	Dow Chemical	AT&T
19	Bell Atlantic	DuPont	Eastman Kodak	RealNetworks	AMR	News Corp
20	America Online	Qualcomm	RealNetworks	Ford	Johnson & Johnson	Andarko Petroleum
21	Unisys	GTE Corp	News Corp	Merck & Co	CBS Corp	Hess Corp
22	Eastman Kodak	Eastman Kodak	Sprint	Qualcomm	DuPont	Google
23	Pacific Telesis	Viacom	Walt Disney	Lockheed Martin	Adobe Systems	Lockheed Martin
24	Rockwell	Ford	CMG Info.	GM	Honeywell	Johnson & Johnson
25	US WEST Inc	3Com	i2 Technologies	VeriSign	ConocoPhillips	Bristol-Myers Squibb

Table 4
Descriptive Statistics

Panel A presents the summary statistics for variables used in my empirical tests. My sample consists of 31,533 U.S. firm-year observations in alliance networks between 1994 and 2013. All network centrality measures are log-transformed to isolate the effect of extreme outliers. See Appendix 2 for the discussion of network centrality measures. All dollar denominated variables are deflated to 2009 dollars using U.S. GDP deflator. All variables are winsorized at the 1st and 99th percentiles, except for *Centrality (*and other centrality measures)*, Size, Age, Price Informativeness, and Probability of Informed Trading (PIN).* See Appendix 1 for the complete list of variable definitions. Panel B shows the correlation coefficients between *Centrality* and a group of key variables.

Panel A: Summary Statistics						
	N	Mean	Std.	P25	Median	P75
Alliance Network Centrality Measures						
Centrality	31,533	1.5702	1.4150	0.2365	1.2636	2.5391
Degree Centrality	31,533	1.0005	1.0469	0	0.6931	1.6094
Indirect Centrality	26,733	0.2410	2.6439	-1.5299	0.4521	2.2939
Centrality High Alliance	15,815	1.1169	1.2325	0	0.7452	1.8123
Centrality Low Alliance	12,977	0.9010	1.0540	0	0.6958	1.4214
Dependent Variables						
CAPEX	31,533	0.0577	0.0697	0.0174	0.0356	0.0694
CAPEX + R&D	31,533	0.1461	0.1574	0.0448	0.0952	0.1891
Control Variables						
Size ($ billion)	31,533	4.7955	24.2855	0.0793	0.3760	2.0754
Age (years)	31,533	19.33	15.36	8	13	27
Q	31,533	2.3225	1.9096	1.2104	1.6729	2.6446
ROA	31,533	0.0274	0.2520	-0.0026	0.0999	0.1607
Leverage	31,533	0.2054	0.2100	0.0130	0.1611	0.3227
Cash	31,533	0.2291	0.2395	0.0366	0.1343	0.3584
R&D	31,533	0.0823	0.1358	0	0.0244	0.1099
Sales Growth	31,533	0.2360	0.7027	-0.0239	0.0923	0.2652
Asset Growth	31,533	0.1971	0.6066	-0.0477	0.0626	0.2238
Return Volatility	31,533	0.0404	0.0236	0.0231	0.0347	0.0510
Price Informativeness	31,533	1.9018	2.2290	0.5009	1.8117	3.3637
Probability of Informed Trading (PIN)	28,322	0.1828	0.0981	0.1130	0.1640	0.2320

Panel B: Correlation Matrix of Key Variables									
Number of Observations: 31,533									
	Centrality	Size	Age	Q	ROA	Leverage	CAPEX	R&D	Cash
Centrality	1								
Size	0.3265	1							
Age	0.0827	0.5263	1						
Q	0.0945	-0.2283	-0.2155	1					
ROA	0.0394	0.5003	0.3005	-0.2608	1				
Leverage	-0.0528	0.2466	0.1310	-0.1550	0.0540	1			
CAPEX	0.0037	0.0550	-0.0669	0.0142	0.0779	0.1297	1		
R&D	0.0874	-0.4092	-0.2688	0.3862	-0.6486	-0.1978	-0.0956	1	
Cash	0.0644	-0.3587	-0.3590	0.3903	-0.4093	-0.3931	-0.1939	0.5406	1

Table 5

Alliance Network Centrality and Investment-to-Price Sensitivity

This table shows the effect of centrality in alliance networks on the investment-to-price sensitivity. The dependent variable is capital expenditure (CAPEX) and measured in percentage points. In Column (1), *Centrality* is a natural logarithm of the Bonacich centrality described in Section 2.3. In Column (2), *Centrality* is an indicator variable that equals 1 if the Bonacich centrality of a firm is above my sample median, 0 otherwise. In Column (3), *Centrality* is the degree centrality discussed in Section 2.2. In Column (4), *Centrality* is a measure that only captures the extent of indirect connections. In Column (5), I control for the probability of informed trading (PIN) instead of stock price informativeness as a proxy for the private information contained in stock prices. See Appendix 1 for the complete list of variable definitions. All specifications include calendar year and firm fixed effects. Standard errors are corrected for heteroskedasticity and clustering at the firm level. *t*-statistics are in parentheses. See Table 4 for the list of winsorized variables. ***, **, and * indicate the statistical significance at 1%, 5%, and 10%, respectively.

Centrality Measure	Bonacich	Indicator	Degree	Indirect	Bonacich
Dependent Variable: CAPEX	(1)	(2)	(3)	(4)	(5)
Centrality	0.047	0.042	0.025	0.010	0.037
	(0.69)	(0.25)	(0.27)	(0.26)	(0.52)
Q	0.817***	0.765***	0.811***	0.704***	0.751***
	(11.44)	(11.46)	(11.80)	(12.31)	(7.24)
Centrality × Q	**-0.060*** **	**-0.124** **	**-0.086*** **	**-0.030** **	**-0.054** **
	(-2.64)	**(-1.97)**	**(-2.71)**	**(-2.08)**	**(-2.25)**
Sales Growth	-0.020	0.072	0.059	0.171**	-0.058
	(-0.19)	(0.74)	(0.62)	(2.55)	(-0.50)
Centrality × Sales Growth	0.106**	0.125	0.077	0.062**	0.111**
	(2.00)	(0.95)	(1.12)	(2.27)	(2.01)
ROA	2.342***	2.594***	2.507***	2.576***	2.612***
	(5.93)	(7.14)	(6.94)	(7.92)	(6.24)
Centrality × ROA	0.205	0.098	0.163	0.059	0.181
	(1.14)	(0.24)	(0.66)	(0.62)	(0.97)
Size	-1.264***	-1.260***	-1.261***	-1.324***	-1.359***
	(-11.16)	(-11.16)	(-11.09)	(-10.93)	(-10.81)
Cash	-0.172	-0.171	-0.202	-0.429	-0.144
	(-0.44)	(-0.44)	(-0.52)	(-1.01)	(-0.35)
Leverage	-3.908***	-3.903***	-3.918***	-3.877***	-3.970***
	(-9.19)	(-9.19)	(-9.24)	(-8.21)	(-9.01)
Price Informativeness	-0.180***	-0.193***	-0.178***	-0.207***	
	(-3.87)	(-4.14)	(-3.80)	(-4.08)	
Price Informativeness × Q	0.002	0.008	0.000	0.010	
	(0.15)	(0.52)	(0.01)	(0.56)	
PIN					-3.722***
					(-3.63)
PIN × Q					0.542
					(1.11)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	No
Observations	31,533	31,533	31,533	26,733	28,322
Within R^2	0.172	0.171	0.172	0.185	0.175

Table 6

Endogeneity: Firm-Cohort Fixed Effects

This table examines the endogeneity issue in my main results using firm-cohort fixed effects that control for endogenous changes in centrality regarding alliance formation (see Section 3.2). The dependent variable is capital expenditure (CAPEX) and measured in percentage points. *Centrality* is a natural logarithm of the Bonacich centrality described in Section 2.3. See Appendix 1 for the complete list of variable definitions. All specifications include calendar year and firm-cohort fixed effects. Standard errors are corrected for heteroskedasticity and clustering at the firm level. *t*-statistics are in parentheses. See Table 4 for the list of winsorized variables. ***, **, and * indicate the statistical significance at 1%, 5%, and 10%, respectively.

Dependent Variable: CAPEX	(1)	(2)
Centrality	0.067	0.056
	(0.64)	(0.48)
Q	0.821***	0.748***
	(10.05)	(6.15)
Centrality × Q	**-0.057***	**-0.059**
	(-1.71)	**(-1.64)**
Sales Growth	-0.242*	-0.258*
	(-1.74)	(-1.70)
Centrality × Sales Growth	0.153*	0.127
	(1.89)	(1.59)
ROA	2.919***	3.348***
	(5.34)	(5.61)
Centrality × ROA	-0.243	-0.278
	(-0.98)	(-1.04)
Size	-2.218***	-2.313***
	(-12.63)	(-11.73)
Cash	2.092***	2.457***
	(4.36)	(4.72)
Leverage	-5.158***	-5.222***
	(-9.10)	(-8.43)
Price Informativeness	-0.067	
	(-1.30)	
Price Informativeness × Q	-0.043**	
	(-2.20)	
PIN		-1.829*
		(-1.69)
PIN × Q		-0.197
		(-0.37)
Year FE	Yes	Yes
Firm-Cohort FE	Yes	Yes
Observations	31,533	28,322
Within R^2	0.113	0.116

Table 7

Alternative Explanations

This table performs additional tests on the effect of centrality in alliance networks on the investment-to-price sensitivity. The dependent variable is capital expenditure (CAPEX) in Columns (1)-(7), and capital plus R&D expenditure (CAPEX + R&D) in Column (8). Columns (1)-(6) test whether my findings are driven by the mispricing component of stock prices rather than the information content in prices. Column 8 includes R&D into a part of the measure of corporate investment. All dependent variables are measured in percentage points. *Centrality* is a natural logarithm of the Bonacich centrality described in Section 2.3. See Appendix 1 for the complete list of variable definitions. *Controls* are from Column (1) of Table 5. All specifications include calendar year and firm fixed effects. Only the coefficients of interest are reported for a parsimony. Standard errors are corrected for heteroskedasticity and clustering at the firm level. *t*-statistics are in parentheses. See Table 4 for the list of winsorized variables. ***, **, and * indicate the statistical significance at 1%, 5%, and 10%, respectively.

Explanations	Mispricing Component?						Non-linearity?	Intangible Capital?
Treatment	WW Index		KZ Index		SA Index		Include Q^2	Dependent Variable:
	High	Low	High	Low	High	Low	in the regression	CAPEX + R&D
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Centrality × Q	0.016	**-0.202*** **	-0.002	**-0.104** **	0.020	**-0.213*** **	**-0.042***	**-0.093** **
	(0.42)	**(-3.47)**	(-0.07)	**(-2.06)**	(0.58)	**(-3.90)**	**(1.87)**	**(-1.97)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,743	10,408	10,714	10,405	10,751	10,413	31,533	22,384
Within R^2	0.111	0.245	0.143	0.143	0.117	0.229	0.176	0.307

Table 8

Robustness Tests

This table tests the robustness of my main results. The dependent variable is capital expenditure (CAPEX) and measured in percentage points. Columns (1) and (2) test the robustness of my results to 3- and 7-year assumptions of alliance duration (see Section 2.2). Columns (3) and (4) test the robustness of my results to alternative parameter choices for the calculation of Bonacich centrality. Columns (5) and (6) test the robustness of my results using two other popular centrality measures, betweenness and eigenvector centrality. See Section 2.3 and Appendix 2 for the discussion of centrality measures. Column (7) only includes firm-year observations with the absolute change in total assets less than or equal to 20%. Column (8) uses centrality measures constructed from alliance networks consisting of alliance deals within the United States. *Centrality* is a natural logarithm of the Bonacich centrality described in Section 2.3. Control variables are from Column (1) of Table 5. See Appendix 1 for the complete list of variable definitions. All specifications include calendar year and firm fixed effects. Only the coefficients of interest are reported for a parsimony. Standard errors are corrected for heteroskedasticity and clustering at the firm level. *t*-statistics are in parentheses. See Table 4 for the list of winsorized variables. ***, **, and * indicate the statistical significance at 1%, 5%, and 10%, respectively.

Robustness	3-year	7-year	Bonacich+	Bonacich-	Betweenness	Eigenvector	$\lvert\Delta A\rvert \leq 20\%$	U.S. Only
Dependent Variable: CAPEX	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Centrality × Q	**-0.051****	**-0.074*****	**-0.044****	**-0.070*****	**-0.282***	**-0.060*****	**-0.056****	**-0.056****
	(-2.01)	**(-3.18)**	**(-2.36)**	**(-2.75)**	**(-1.91)**	**(-3.21)**	**(-2.38)**	**(-2.18)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,427	31,028	31,533	31,533	31,533	31,533	19,975	25,925
Within R^2	0.169	0.168	0.172	0.172	0.172	0.172	0.139	0.178

Table 9

More vs. Less Integrative Forms of Alliances

This table compares the effect of alliance network centrality in two sub-networks based on the level of integration. The dependent variable is capital expenditure (CAPEX) and measured in percentage points. See Appendix 1 for the complete list of variable definitions. All specifications include calendar year and firm fixed effects. Standard errors are corrected for heteroskedasticity and clustering at the firm level. *t*-statistics are in parentheses. See Table 4 for the list of winsorized variables. ***, **, and * indicate the statistical significance at 1%, 5%, and 10%, respectively.

Dependent Variable: CAPEX	(1)	(2)	(3)
Centrality High Alliance	0.091		0.132
	(0.93)		(0.86)
Centrality Low Alliance		0.157	0.077
		(1.38)	(0.57)
Q	0.629***	0.655***	0.551***
	(8.37)	(7.20)	(4.26)
Centrality High Alliance × Q	**-0.057***		-0.063
	(-1.81)		(-1.64)
Centrality Low Alliance × Q		-0.067	0.011
		(-1.57)	(0.22)
Sales Growth	-0.023	0.330**	0.321
	(-0.16)	(2.27)	(1.18)
Centrality High Alliance × Sales Growth	0.306***		0.344**
	(2.89)		(2.29)
Centrality Low Alliance × Sales Growth		-0.067	-0.142
		(-0.75)	(-1.03)
ROA	1.951***	2.377***	2.210**
	(3.73)	(4.29)	(2.32)
Centrality High Alliance × ROA	0.963***		1.348***
	(2.93)		(2.91)
Centrality Low Alliance × ROA		0.190	-0.730
		(0.45)	(-1.23)
Size	-1.368***	-1.446***	-1.591***
	(-7.86)	(-8.63)	(-6.67)
Cash	0.344	-0.070	0.081
	(0.65)	(-0.12)	(0.10)
Leverage	-3.424***	-3.579***	-2.596***
	(-6.07)	(-5.27)	(-2.80)
Price Informativeness	-0.311***	-0.222***	-0.399***
	(-4.87)	(-3.02)	(-3.62)
Price Informativeness × Q	0.026	0.027	0.066*
	(1.25)	(1.08)	(1.71)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	15,815	12,977	6,486
Within R^2	0.201	0.204	0.247

Table 10

Alliance Network Centrality and Market Valuations

This table shows the effect of centrality in alliance networks on market valuations. The dependent variable is Tobin's Q. *Centrality* is a natural logarithm of the Bonacich centrality described in Section 2.3. See Appendix 1 for the complete list of variable definitions. All specifications include calendar year and firm (or firm-cohort) fixed effects. Standard errors are corrected for heteroskedasticity and clustering at the firm level. *t*-statistics are in parentheses. See Table 4 for the list of winsorized variables. ***, **, and * indicate the statistical significance at 1%, 5%, and 10%, respectively.

Dependent Variable: ΔQ	(1)	(2)	(3)	(4)	(5)
Centrality	0.011	0.018			
	(0.73)	(0.68)			
Centrality High Alliance			**0.059*** **		0.002
			(2.60)		(0.05)
Centrality Low Alliance				0.033	0.012
				(0.97)	(0.29)
Size	-0.597***	-0.688***	-0.696***	-0.796***	-0.844***
	(-17.45)	(-14.62)	(-13.65)	(-14.97)	(-10.55)
Age	-0.430***	-0.166	-0.343**	-0.444***	-0.249
	(-5.08)	(-1.20)	(-2.57)	(-3.01)	(-1.05)
ROA	0.502***	0.159	0.745***	0.851***	1.107***
	(3.95)	(1.18)	(3.75)	(4.30)	(3.14)
R&D	2.065***	0.696**	2.049***	1.997***	1.998***
	(7.52)	(2.12)	(5.27)	(4.37)	(2.92)
CAPEX	-0.021	-1.117***	-0.458	-0.737	-0.692
	(-0.07)	(-3.46)	(-0.93)	(-1.44)	(-0.78)
Cash	0.786***	0.333**	0.557***	0.946***	0.737**
	(5.97)	(2.42)	(2.97)	(4.62)	(2.34)
Leverage	0.186*	0.298**	0.036	0.014	-0.065
	(1.70)	(2.34)	(0.24)	(0.08)	(-0.24)
Return Volatility	-2.015**	-0.351	0.930	-3.856**	-1.930
	(-2.17)	(-0.36)	(0.66)	(-2.51)	(-0.68)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	Yes	Yes
Firm-Cohort FE	No	Yes	No	No	No
Observations	31,533	31,533	15,815	12,977	6,486
Within R^2	0.151	0.096	0.166	0.190	0.213

Table 11

Summary of Alliance Announcements

This table reports the summary statistics for alliance announcements. The sample consists of 4,122 announcements between two public U.S. firms (8,244 firm-level observations) from 1994 through 2013. All dollar denominated variables are deflated to 2009 dollars using U.S. GDP deflator. CAR is estimated on a three-day (-1, 1) window using market-adjusted returns from CRSP value-weighted index. *Centrality* is a natural logarithm of the Bonacich centrality described in Section 2.3. See Appendix 1 for the complete list of variable definitions. Alliance types are based on SDC classifications and not mutually exclusive (total may exceed or be less than 100%).

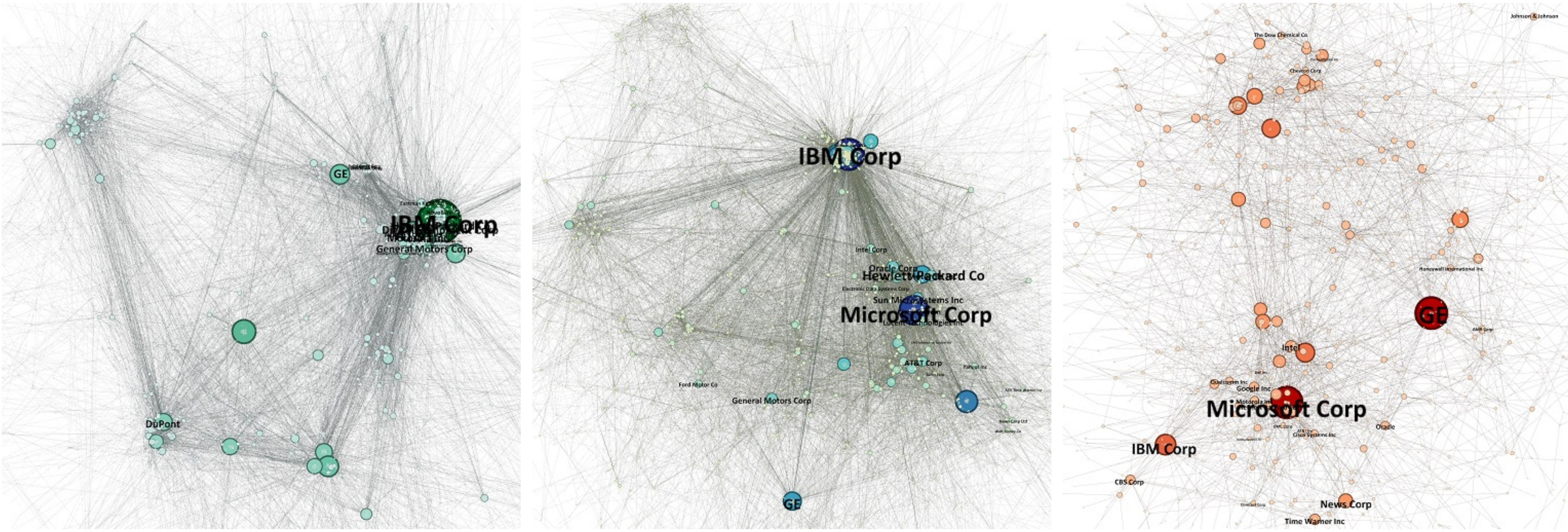
	Obs.	Mean	Std.	P25	Median	P75
CAR (%)	8,244	1.194	8.697	-2.222	0.188	3.097
Dollar Wealth Gain ($ million)	8,244	18.840	3,808.158	-115.675	1.430	131.861
CAR by Alliance Type (%)						
High Alliance	2,174	0.889	6.486	-1.933	0.107	2.819
Low Alliance	1,758	1.797	9.845	-2.107	0.346	3.587
Other Alliance (no types reported)	4,312	1.102	9.131	-2.390	0.171	3.115
CAR by Partner Relation (%)						
Horizontal	2,340	1.791	10.053	-2.306	0.445	3.712
Non-horizontal	5,904	0.957	8.070	-2.177	0.111	2.902
Controls						
Centrality	8,244	3.653	2.003	2.115	3.629	5.197
High Alliance	8,244	0.264	0.441	0	0	1
Low Alliance	8,244	0.213	0.410	0	0	0
Horizontal	8,244	0.284	0.451	0	0	1
Size ($ billion)	8,244	37.729	127.484	0.346	3.718	26.327
Age (years)	8,244	23.587	18.198	8	16	45
ROA	8,244	0.084	0.200	0.045	0.124	0.187
R&D	8,244	0.085	0.111	0	0.052	0.119

Table 12

Alliance Network Centrality and Announcement Effects

This table investigates whether higher alliance network centrality leads to more positive market reactions to the announcement of alliances. The dependent variable is three-day (-1, 1) CAR using market-adjusted returns from CRSP value-weighted index. CAR is measured in percentage points. *Centrality* is a natural logarithm of the Bonacich centrality described in Section 2.2. See Appendix 1 for the complete list of variable definitions. All specifications include calendar year fixed effects. Standard errors are corrected for heteroskedasticity and clustering at the firm level. *t*-statistics are in parentheses. ***, **, and * indicate the statistical significance at 1%, 5%, and 10%, respectively.

Dependent Variable: 3-day CAR	(1)	(2)	(3)	(4)
Centrality	-0.031			
	(-0.44)			
Centrality High Alliance		**0.180****		**0.344***
		(2.20)		**(1.94)**
Centrality Low Alliance			0.130	-0.043
			(1.45)	(-0.28)
Partner Centrality	**0.115***			
	(1.79)			
Partner Centrality High Alliance		**0.135***		**0.291****
		(1.71)		**(2.53)**
Partner Centrality Low Alliance			0.111	-0.113
			(1.20)	(-0.85)
High Alliance	-0.134	-0.032	-0.207	-0.302
	(-0.71)	(-0.13)	(-0.84)	(-1.06)
Low Alliance	0.595**	0.456	0.460	0.250
	(2.13)	(1.25)	(1.27)	(0.55)
Horizontal	0.371	0.336	0.147	0.220
	(1.54)	(1.20)	(0.49)	(0.63)
Size	-0.311***	-0.446***	-0.393***	-0.547***
	(-4.22)	(-3.94)	(-3.60)	(-3.30)
Age	0.229	0.312	0.509*	0.482
	(1.34)	(1.24)	(1.94)	(1.34)
ROA	-5.397***	-5.655***	-8.182***	-6.433**
	(-4.97)	(-3.38)	(-4.35)	(-2.50)
R&D	4.270**	3.046	2.864	2.539
	(2.31)	(1.19)	(1.00)	(0.68)
Partner Size	0.266***	0.211**	0.380***	0.234**
	(4.20)	(2.38)	(4.69)	(2.40)
Partner Age	-0.306**	-0.354*	-0.449**	-0.402*
	(-2.04)	(-1.81)	(-2.25)	(-1.76)
Partner ROA	0.558	0.943	0.222	0.897
	(0.91)	(1.21)	(0.27)	(0.91)
Partner R&D	0.125	-0.380	0.927	0.646
	(0.12)	(-0.31)	(0.71)	(0.39)
Year FE	Yes	Yes	Yes	Yes
Observations	8,244	4,684	4,560	3,024
Adjusted R^2	0.057	0.055	0.062	0.052



(A) Network in 1994

Number of nodes: 22,373

(B) Network in 2002

Number of nodes: 34,982

(C) Network in 2010

Number of nodes: 22,670

Figure 1

Snapshot of Alliance Networks

This figure illustrates the snapshot of alliance networks for selected years. Each illustration consists of points (nodes) and lines (edges). I use Gephi 0.9.1 to visualize networks with the "OpenOrd" layout specialized in distinguishing clusters in undirected graphs. The size of points indicates the degree (the number of direct connections) of each node. Each snapshot shows the location of 25 key firms listed in Table 3.

Appendix 1: Variable definitions

Variables	Description	Source
Centrality	A natural logarithm of the Bonacich centrality. See the Appendix 2 for an introduction of the Bonacich centrality.	SDC
Centrality High Alliance	A natural logarithm of the Bonacich centrality in networks of joint ventures, R&D agreements, (cross-) technology transfer agreements, and manufacturing agreements, excluding alliances overlapping Low Alliance	
Centrality Low Alliance	A natural logarithm of the Bonacich centrality in networks of (cross-) licensing agreements and marketing agreements, excluding alliances overlapping with High Alliance	
High Alliance	An indicator variable which equals 1 if alliances are joint ventures, R&D agreements, (cross-) technology transfer agreements, or manufacturing agreements, excluding alliances overlapping Low Alliance	
Low Alliance	An indicator variable which equals 1 if alliances are (cross-) licensing agreements and marketing agreements, excluding alliances overlapping with High Alliance	
Horizontal	An indicator variable which equals 1 if alliances are formed between two firms operating in the same SIC 3-digit industry	
Size	A natural logarithm of Total Assets (**at**), deflated to 2009 dollars using U.S. GDP deflator from Bureau of Economic Analysis	Compustat
Age	A natural logarithm of the firm age defined as 1 plus the number of years appearing in Compustat	
Leverage	[Short-term Debt (**dlc**) + Long-term Debt (**dltt**)] / Total Assets (**at**)	
Q	[Total Assets (**at**) – Common Equity (**ceq**) + (Common Share Price (**prcc_f**) * Common Shares Outstanding (**csho**))] / Total Assets (**at**). If **prcc_f** is missing, I use the price (**prc**) at the last trading date of the fiscal year from CRSP.	
Cash	Cash and Short-term Investments (**che**) / Total Assets (**at**)	
ROA	Operating Income Before Depreciation and Amortization (**oibdp**) / Total Assets (**at**)	
R&D	Research and Development Expenditure (**xrd**) / Total Assets (**at**). For the investment regression, **xrd** is scaled by the lagged Total Assets ($\mathbf{at}_{-1}$).	
CAPEX	Capital Expenditure (**capx**) / Total Assets (**at**). For the investment regression, **capx** is scaled by the lagged Total Assets ($\mathbf{at}_{-1}$).	
Asset Growth	Change in Total Assets ($\mathbf{at} - \mathbf{at}_{-1}$)/ lagged Total Assets ($\mathbf{at}_{-1}$)	
Sales Growth	Change in Sales ($\mathbf{sale} - \mathbf{sale}_{-1}$)/ lagged Sales ($\mathbf{sale}_{-1}$)	
Cash Flow Volatility	Standard deviation of cash flows for the previous 10 years. I require at least three observations.	
Dividends	Common Dividends (**dvc**) / Total Assets (**at**)	
Dividend Payer	An indicator variable which equals 1 if Dividends > 0, 0 otherwise	
WW Index	Whited and Wu (2006): -0.091 * CF – 0.062 * Dividend Payer +	

	0.021 * Long-term Debt (**dltt/at**) – 0.044 * Size + 0.102 * Industry Sales Growth (SIC 3-digit) – 0.035 * Firm Sales Growth	
KZ Index	Lamont, Polk, and Saá-Requejo (2001): –1.001909 * CF + 0.2826389 * Q + 3.139193 * Book Leverage – 39.3678 * Dividends – 1.314759 * Cash	
SA Index	Hadlock and Pierce (2010): –0.737 * Total Assets + 0.043 * Total Assets^2 – 0.04 * (1 + the number of years appearing in Compustat). Total Assets are deflated to 2009 dollars using U.S. GDP deflator from BEA.	
SIC	SIC industry classifications. I primarily use the Compustat historical SIC code (**sich**). I use the first non-missing **sich** for the all prior fiscal years with missing **sich**. If **sich** is still missing, I use the CRSP historical SIC code (**siccd**).	
Combined Reporting	Bodnaruk, Massa, and Simonov (2013): Average of subsidiary-level combined reporting indicator variables within the same SIC 4-digit industry (excluding the firm itself from the computation). For each subsidiary of firm, a combined reporting indicator variable equals 1 if the subsidiary is operated in the state that requires combined reporting rules for corporate income taxes, 0 otherwise.	Compustat Dun & Bradstreet
Return Volatility	Standard deviation of daily stock returns calculated annually. I require at least 30 observations.	CRSP
Price Informativeness	Foucault and Fresard (2014): log (1 – R^2 / R^2) where R^2 is R-square from the regression of daily firm return on market and industry (SIC 3-digit) value-weighted portfolio returns. Regressions are estimated each calendar year. I drop the measure calculated from less than 30 daily observations.	
Probability of Informed Trading (PIN)	Probability of informed trading based on Brown and Hillegeist (2007). Annual firm-level observations between 1993 and 2010 are available at Stephen Brown's website.	

Appendix 2: Details of network centrality measures

This appendix introduces the idea and mathematical formulation of Bonacich centrality (Bonacich 1987), and reports additional descriptive statistics of centrality measures used in this paper. See Chapter 2 of Jackson (2008) for a textbook introduction to centrality measures.

Consider a network consists of n different nodes (members). Let denote $\boldsymbol{G}$ as an $n \times n$ adjacency matrix which has an element of unity if two nodes are connected, and zero otherwise. Also denote $\mathbf{1}$ as an $n \times 1$ vector of ones. Define a walk as a direct connection from one to another node in the network. Then $\boldsymbol{G}\mathbf{1}$ indicates the number of walks emanating from each node, i.e., the degree of each node. Furthermore, $\boldsymbol{G}\boldsymbol{G}\mathbf{1} = \boldsymbol{G}^2\mathbf{1}$ indicates the number of *indirect* connections from each node where an indirect connection consists of two walks. For example, if $n = 4$ and the third element of $\boldsymbol{G}^2\mathbf{1}$ is 2, then Node 3 can reach two other nodes in the network via two walks, such as (3 → 1 → 2) and (3 → 4 → 1). Likewise, $\boldsymbol{G}^k\mathbf{1}$ indicates the number of indirect connections from each node where an indirect connection consists of k walks.

The idea of the Bonacich centrality resides in that the influence of a node is determined by the number of all direct and indirect connections emanating from the node. Suppose that there is a scalar β which is a decaying factor that discounts the extent of influence for each additional walk. Then the influence of a node can be represented as the weighed sum of all connections emanating from the node. If we denote $\boldsymbol{P}$ as a vector of nodes' influence, then

$$\boldsymbol{P} = \boldsymbol{G}\mathbf{1} + \beta\boldsymbol{G}^2\mathbf{1} + \beta^2\boldsymbol{G}^3\mathbf{1} + \cdots \tag{A1}$$

$$\boldsymbol{P} = (\mathbf{1} + \beta\boldsymbol{G} + \beta^2\boldsymbol{G}^2 + \cdots)\boldsymbol{G}\mathbf{1} = (\boldsymbol{I} - \beta\boldsymbol{G})^{-1}\boldsymbol{G}\mathbf{1} \tag{A2}$$

Notice that $\boldsymbol{P}$ is well-defined for a sufficiently small β. Bonacich (1987) suggests that β must be less in absolute value than the reciprocal of the largest eigenvalue of $\boldsymbol{G}$. I follow Robinson and Stuart (2007b) to set β to be three-quarters of the largest eigenvalue of $\boldsymbol{G}$.

The Bonacich centrality $\boldsymbol{C}$ is simply a scaled vector of nodes' influence,

$$\boldsymbol{C} = \alpha\boldsymbol{P} = \alpha(\boldsymbol{I} - \beta\boldsymbol{G})^{-1}\boldsymbol{G}\mathbf{1} \tag{A3}$$

where α is a scaling parameter that allows an adjustment in the base degree of nodes according to network characteristics, such as network size and density.

Table A1 compares the summary statistics across centrality measures used in my paper: degree, Bonacich-, Bonacich, Bonacich+, eigenvector, and betweenness centrality. All centrality values are log-transformed. Panel A confirms that Bonacich measures capture the indirect connections that the degree centrality is unable to do. From the degree centrality to the Bonacich+ centrality, both the mean and standard deviation monotonically increase. This result is consistent with the idea that the value of indirect connections is increasing: from zero in the degree centrality to the largest in Bonacich+.

Panel B reports the correlation between all centrality measures. It is worth noting that the correlation with degree centrality becomes lower as the Bonacich centrality assigns more weight (increase β) on indirect connections on the network. Consequently, eigenvector centrality in this paper is the measure that more emphasizes the impact of indirect connections, which is consistent with the measurement focus on the relative importance of nodes in the network. Interestingly, the correlation between the betwenness centrality and other centrality measures is among the lowest. This might be because the betweenness centrality assumes that information can flow only along the shortest paths between nodes.

Table A1

Summary of Centrality Measures

This table summarizes centrality measures used in this paper. All centrality measures are log-transformed. Panel A reports summary statistics. Panel B shows the correlation between centrality measures.

Panel A: Descriptive Statistics						
Number of Observations: 31,533						
	N	Mean	Std.	P25	Median	P75
Degree	31,533	1.0005	1.0469	0	0.6931	1.6094
Bonacich- (0.8β)	31,533	1.3966	1.2756	0.1519	1.1447	2.2174
Bonacich	31,533	1.5702	1.4150	0.2365	1.2636	2.5391
Bonacich+ (1.2β)	31,533	1.9172	1.7085	0.4053	1.5197	3.1411
Eigenvector	31,533	-5.8700	1.7779	-7.3060	-6.1356	-4.4938
Betweenness	31,533	0.1236	0.3097	0	0.0053	0.1099

Panel B: Correlation Matrix						
Number of Observations: 31,533						
	Degree	Bonacich-	Bonacich	Bonacich+	Eigenvector	Betweenness
Degree	1					
Bonacich-	0.9302	1				
Bonacich	0.8943	0.9955	1			
Bonacich+	0.8363	0.9742	0.9910	1		
Eigenvector	0.7973	0.9319	0.9465	0.9501	1	
Betweenness	0.7423	0.6722	0.6407	0.5901	0.5851	1