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Alliance Networks, Corporate Investment, and Firm Valuation

Sangho Lee

Alliance Networks, Corporate Investment, and Firm Valuation

BY

Sangho Lee

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ACCEPTANCE

This dissertation was prepared under the direction of the Sangho Lee's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

Richard Phillips, Dean

DISSERTATION COMMITTEE

Dr. Omesh Kini (Chair)
Dr. Mark A. Chen
Dr. Dalida R. Kadyrzhanova
Dr. Sudheer Chava (External: Georgia Tech)

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My wife, Yunhee, and I share every single moment of my Ph.D. student years. Her love and companionship made this work possible. I dedicate this dissertation to her.

ABSTRACT

Alliance Networks, Corporate Investment, and Firm Valuation

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June 20, 2017

Committee Chair: Dr. Omesh Kini

Major Academic Unit: Department of Finance

This paper examines whether corporate alliance networks convey information about new investment opportunities. I hypothesize that firms located more centrally in their networks are exposed to greater information flows, which allows managers to rely less on their own stock prices as a source of information to make future investment decisions. Supporting this prediction, higher alliance network centrality leads to lower sensitivity of investment to stock prices. The impact is stronger for financially unconstrained firms, showing that financial constraints may limit firms' ability to exploit their informational advantages from alliance networks. Additional tests exploiting quasi-exogenous changes in centrality due to indirect connections via alliance partners alleviate the endogeneity issue in alliance formation decision. The stock market reacts more positively to alliance announcements when new alliances are expected to provide greater informational benefits. Overall, my results show that alliance networks are conduits for value-enhancing information that affect corporate investment decision and valuation.

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1. Introduction

Corporate alliances are collaborative organizational structures on an intermediate point on the market-hierarchy continuum of firm boundary choices (Williamson 1975) that includes a variety of contractual forms such as joint ventures, (cross-) licensing agreements, manufacturing agreements, marketing agreements, and research and development (R&D) agreements. Alliances promote tighter connections between partners than arm's length market transactions (Johnson and Houston 2000) without sacrificing organizational flexibility (Chan, Kensinger, Keown and Martin 1997), thereby enhancing firm value and performance.[1] One important source of gain stems from reducing the cost of transferring knowledge between partners (Jensen and Meckling 1992). Specifically, partners in alliances can have easier access to other members' information resources (Mowery, Oxley and Silverman 1996), which can increase knowledge flows between partners (Gomes-Casseres, Hagedoorn and Jaffe 2006). Moreover, alliances establish channels of private communication between managers (Robinson and Stuart 2007) who can then obtain new information and incorporate it in corporate decisions. For example, alliance connections can be conduits for conveying information about future investment opportunities, thereby influencing corporate investment decisions.

This paper empirically tests this idea using network analysis on a large sample of corporate alliances. I use network analysis to model the structure of information transmission not only between alliance partners, but also all firms indirectly connected through the chain of alliance connections. Alliance networks may transmit a variety of information about technology-related knowledge, product or geographic market prospects, human capital, and more general economic conditions, which can eventually help managers detect future investment opportunities. More connected firms have access to a wider range of knowledge resources available over the networks (Schilling and Phelps 2007), and may thus possess informational advantages vis-à-vis less connected firms in the networks. This paper shows that these informational advantages have

[1] For example, the stock market positively reacts to announcements of joint ventures (Johnson and Houston 2000; McConnell and Nantell 1985) and strategic alliances (Chan, Kensinger, Keown and Martin 1997). Schilling (2015) provide evidence that alliances lead to more innovation outcomes.

a value-enhancing effect on investment decisions, thereby supporting the argument that managers can learn valuable information from alliance networks and subsequently use this information when making investment decisions.

I construct time-varying networks of alliances between 1994 and 2013 using a large sample of alliance deals from the Thomson Reuters SDC Platinum Joint Venture and Strategic Alliance Database (SDC). An alliance network is a snapshot of all ongoing alliance connections at the end of each calendar year. For each firm in an alliance network, I calculate the Bonacich measure of power and centrality ("Bonacich centrality") (Bonacich 1987) as a measure of network centrality that proxies for the firm's informational advantages. This measure offers two important benefits for my research objectives. First, it provides measurement flexibility to handle fluctuations in the size and density of time-varying networks. Second, the measure can be decomposed into direct and indirect components of connections. Thus, I can design a test to isolate the impact of *direct* connections which create identification issues due to the endogenous nature of alliance formation decisions. [2]

Using time-varying alliance networks and Bonacich centrality, I find that firms with a higher alliance network centrality show a lower sensitivity of investment to Tobin's Q, a measure of price-based investment opportunities. The investment-to-price sensitivity of central (at the 75th percentile of centrality distribution) firms is about 20% less than that of non-central firms (at the 25th percentile). This finding is consistent with the argument that more centrally located firms in alliance networks are exposed to greater information flows, which then allows managers to rely less on their stock prices as a source of information for making future investment decisions. The negative relation between alliance network centrality and investment-to-price sensitivity remains significant after controlling for the amount of private information in stock prices and the extent of corporate diversification, which can generate the same empirical predictions without the channel of information flows from alliance networks (Chen, Goldstein and Jiang 2007). In

[2] I provide details regarding the Bonacich measure of centrality in Section 3.2.

addition, I use the Securities and Exchange Commission (SEC)'s Regulation SHO that contains a pilot program that reduces the cost of short selling for a limited period (Fang, Huang and Karpoff 2016) as an exogenous shock that can increase the information in stock prices from which managers can learn and, thus, reduce their needs to learn from alliance networks. Consistent with this argument, the exogenous increase in stock price efficiency adversely affects the negative relation between alliance network centrality and investment-to-price sensitivity.

Previous research shows that financially constrained firms may have limited ability to respond to their investment opportunities immediately due to financial market frictions (Fazzari, Hubbard and Petersen 1988). Thus, I examine whether financial constraints limit firms' ability to exploit their informational advantages from alliance networks and thereby dampen the negative relation between alliance network centrality and investment-to-price sensitivity. Consistent with the prediction, I find that the negative relation between alliance network centrality and investment-to-price sensitivity is stronger for financially unconstrained firms using both sub-sample tests with different proxies for financial constraints as well as an exogenous and negative shock on firms' financial constraints at the onset of the recent financial crisis.

Alliance formation is likely endogenously determined with other corporate policies, thereby creating bias in the estimated coefficients from the OLS regressions. To address the endogeneity concern, I first conduct two tests using quasi-exogenous changes in alliance network centrality due to changes in indirect connections via alliance partner firms.[3] My first test follows a similar strategy as in Anjos and Fracassi (2015) who focus on the within-firm variation in the alliance network centrality of firm-year observations without the initiation of new alliances. Second, following Larcker, So and Wang (2013), I test the impact of the *indirect* part of alliance network centrality, which is likely to be relatively exogenous, on investment-to-price sensitivity using a sub-sample of firms with no changes in their direct alliance connections. Finally, I address the self-selection issue that not all firms participate in alliance networks using exogenous state-

[3] Ideally, a natural experiment that only affects alliance network centrality can effectively establish causality from centrality to investment decisions. Unfortunately, such experiment is extremely hard to find, as Robinson and Stuart (2007) suggest.

level variation in corporate income reporting requirement as an instrument to predict alliance participation (Bodnaruk, Massa and Simonov 2013). The estimated coefficients from all tests are consistent with my argument that alliance networks provide alternative sources of information to make investment decisions, and thus reduce the need for managers to learn from their stock prices.

There is a considerable level of heterogeneity in organizational forms and activities across alliances. My analysis shows that licensing, R&D, and technology transfer agreements are likely to occur between firms operating in an R&D-intensive environment (R&D-related alliances), while joint ventures, marketing, and manufacturing agreements are more popular in less R&D-intensive environments. Consistent with the idea that R&D-related alliances provide more useful information about R&D investment rather than capital expenditure, the relation between alliance network centrality and R&D investment-to-price sensitivity is stronger for firms engaging in more R&D-related alliances.

I perform several additional tests to check the sensitivity of my findings to alternative regressions and network specifications. Existing studies of investment regressions with Tobin's Q show that the estimated OLS coefficients suffer from measurement errors because Tobin's Q can only imperfectly proxy for true but unobservable firm-level investment opportunities (Erickson and Whited 2000; Erickson and Whited 2002). My findings remain similar using the Erickson, Jiang and Whited (2014) cumulant estimator, which addresses measurement errors in panel regressions. I also find similar results using alternative measures of price-based investment opportunities such as Total Q (Peters and Taylor 2017) or industry-level Q. My results are robust to non-linearity in investment-to-price sensitivity or additional firm characteristics and sample selection criteria. I also show that my results are robust to alternative assumptions about alliance durations and alternative measures of network centrality.[4,]

[4] The SDC rarely reports the date of alliance termination, while most alliances last longer than the year of the alliance announcement.

Finally, I examine the association between alliance network centrality and firm value using panel regressions and event study analysis. First, if central firms in alliance networks possess informational advantages vis-à-vis peripheral firms in the networks, they should have better ability to select value-enhancing projects. Consistent with this argument, I find that alliance network centrality is positively related to firm value (measured by Tobin's Q), and the relation becomes statistically significant for financially unconstrained firms. Alliance network centrality positively affects value changes when the firm faces industry-specific shocks, thereby showing that alliance networks convey valuable information that helps managers better anticipate future industry conditions. Second, my event study analysis documents higher announcement-period wealth effects when the increase in alliance network centrality due to new alliances is greater. This result shows that the stock market positively evaluates the greater access to information resources through alliance networks. Additionally, there is a higher value-creation at the alliance-level when announcing firms are already central in alliance networks, which suggests that the market expects greater synergies from alliances between firms with greater informational advantages.

This paper adds to several strands of the literature. First, this paper's most direct contribution is related to corporate alliances. The existing body of alliance research examines the determinants of alliances (Bodnaruk, Massa and Simonov 2013; Campbell, Galpin and Johnson 2016; Lindsey 2008; Stonitsch 2014; Villalonga and McGahan 2005), announcement effects of alliances (Chan, Kensinger, Keown and Martin 1997; Johnson and Houston 2000; McConnell and Nantell 1985), changes in operating and innovation performance (Allen and Phillips 2000; Schilling 2015; Schilling and Phelps 2007), contractual forms of alliances (Mathews 2006; Robinson 2008; Robinson and Stuart 2007), and spillover effects between alliance partners (Boone and Ivanov 2012; Cao, Chordia and Lin 2016). The evidence from this paper characterizes alliances as a channel for learning new information that affects corporate investment decisions, thus adding to the existing literature on the role of alliances in information sharing and knowledge transfer between partners (Gomes-Casseres, Hagedoorn and Jaffe 2006; König, Liu and Zenou 2014; Mowery, Oxley and Silverman 1996).

This paper also fits into the recently growing literature on the informational role of financial markets in corporate investment policies. Specifically, managers can learn from the information contained in their firm's stock prices and incorporate it into investment decisions (Dow and Gorton 1997). Existing evidence shows that the amount of private information contained in stock prices (Chen, Goldstein and Jiang 2007), the intensity of informed trading (Chen, Huang, Kusnadi and Wei 2014; Edmans, Jayaraman and Schneemeier 2016; Foucault and Frésard 2012), and product-market competitors' stock prices (Dessaint, Foucault, Frésard and Matray 2016; Foucault and Fresard 2014) affect investment-to-price sensitivity. My results complement these findings by showing that the information flows through alliance connections can allow managers to rely less on price-based investment opportunities in making investment decisions, and thus reduce investment-to-price sensitivity.

Most broadly, this paper contributes to the literature on network analysis application in financial economics. Network analysis has become increasingly popular in modelling industry- (Ahern 2013; Ahern and Harford 2014; Anjos and Fracassi 2015) or firm-level (Gao 2015) input-output structures, product market rivalry (Hoberg and Phillips 2016), and information transmission through board connections (Fracassi 2016; Larcker, So and Wang 2013) or personal connections among investors (Ahern 2016). While the economics and management literature contains studies of alliance networks (Hagedoorn 2002; König, Liu and Zenou 2014; Rosenkopf and Schilling 2007; Schilling 2015; Schilling and Phelps 2007), this paper is the first to build alliance networks to analyze their informational roles and impact on corporate investment decisions and valuation. I also highlight the benefit of using Bonacich centrality to handle substantially time-varying networks and endogeneity in network participation.

The remainder of this paper proceeds as follows. Section 2 develops the hypotheses. Section 3 describes the data and variables in the empirical tests. Sections 4 and 5 examine the impact of alliance network centrality on corporate investment decisions and the value-implication of alliance network centrality. Section 6 concludes the paper.

2. Related literature and hypotheses development

Corporate alliances are often considered an intermediate point on the market-hierarchy continuum of firm boundaries (Williamson 1975). Specifically, alliances offer a tighter connection between firms than discrete market transactions while the firms maintain separate ownership and control structures, in contrast to full integration. Jensen and Meckling (1992) point out that a network-form of organizations such as alliances can ease the costly transfer of knowledge among members. Consistent with this argument, other studies show the informational benefits of better access to partners' knowledge resources (Mowery, Oxley and Silverman 1996) and greater knowledge transfer between partners (Gomes-Casseres, Hagedoorn and Jaffe 2006), which leads to a relationship between alliances and better operating performance (Allen and Phillips 2000) and innovation outcomes (Li, Qiu and Wang 2016; Schilling 2015; Schilling and Phelps 2007).

While the previous alliance literature largely focuses on bilateral alliances, this paper investigates a more comprehensive impact of informational benefits from alliances using network analysis. Network analysis is an effective tool for modelling information transmission through *both* direct and indirect connections in networks (Jackson 2008). It is worth noting that accounting for "indirect" connections implies that alliances can convey not only alliance-specific knowledge but also more general information such as industry or economic conditions. Thus, a firm's position in an alliance network determines the degree of exposure to information flows through the networks, captured by the measure of network "centrality." A growing body of literature uses centrality in a variety of networks to model the information structure among network members. For example, Anjos and Fracassi (2015) use industry-level input-output networks to proxy for the information structure embedded in the economy. This paper adopts a similar view and estimates the extent of informational advantages from alliance networks using the measure of network centrality.

This paper has three research objectives. I first examine whether and how alliance network centrality affects corporate investment decisions. Second, I investigate the influence of financial constraints on the relation between alliance network centrality and investment decisions. Finally, I study the relation between alliance network centrality and firm value to test whether alliance networks are conduits for conveying value-enhancing information.

I develop four testable hypotheses. First, I predict that higher alliance network centrality lowers the sensitivity of investment to Tobin's Q, a measure of price-based investment opportunities. Dow and Gorton (1997) propose that managers can learn from their own stock prices since stock prices not only reflect the outcome of past investment decisions but also send informative signals about future investment opportunities. Learning from the stock market has become an important research topic regarding the real effects of financial markets (Bond, Edmans and Goldstein 2012). For example, Chen, Goldstein and Jiang (2007) find a higher investment-to-price sensitivity when stock price is more likely to contain private information from informed traders. They conclude that managers can learn more from these more informative stock prices. Managerial learning can stem from other sources of information such as the stock prices of their product market competitors (Foucault and Fresard 2014). Alliance networks may convey useful and publicly unavailable information about future investment opportunities because they offer links of private communication (Robinson and Stuart 2007) in pursuing risky projects (Robinson 2008) that require a certain level of secrecy. In this case, the investment decisions of firms more central in alliance networks may depend less on price-based investment opportunities due to their informational advantages from the networks.[5] This discussion leads to the first hypothesis:

Hypothesis 1. Firms with a higher alliance network centrality exhibit a lower investment-to-price sensitivity.

My second hypothesis is on the influence of financial constraints on the relation between alliance network centrality and investment decisions. Many studies of orporate investment show that financially constrained firms have limited ability to immediately respond to their investment opportunities due to frictions in financial markets (Fazzari, Hubbard and Petersen 1988). For

[5] In a recent theoretical work, Schneemeier (2016) shows that core-firms in a core-periphery network can make more efficient investment decisions because they can extract more accurate information from the financial market. This paper is similar, though focuses on an alternative source of information available outside the market, while Schneemeier (2016) examines information sources from inside the market.

example, Chen, Goldstein and Jiang (2007) find that a stronger positive impact from the amount of private information in stock prices on investment-to-price sensitivity for large firms than for small firms. They interpret the results as evidence that large firms are less likely to have financial constraints and have a better ability to incorporate new information from the stock market immediately in their investment decisions. Similarly, central and financially unconstrained firms in alliance networks should more easily translate their informational advantages into actual investments. This leads to the second hypothesis:

Hypothesis 2. The negative impact of alliance network centrality on investment-to-price sensitivity is stronger for financially unconstrained firms.

Finally, I examine the value-implication of alliance network centrality. If alliance networks convey useful and publicly unavailable information about future investment opportunities, central firms in alliance networks possess informational advantages vis-à-vis peripheral firms in the networks. If these informational advantages are value-enhancing, alliance network centrality will have a positive association with firm value because more centrally located firms in alliance networks should have better ability to select value-maximizing projects. Furthermore, the informational benefit from new alliances should be greater when new alliances are expected to further increase the announcing firms' alliance network centrality. I predict that the stock market positively evaluates the increase in firms' exposure to information flows via alliance networks. Thus, my third and fourth hypotheses state that:

Hypothesis 3. Alliance network centrality is positively associated with firm value.

Hypothesis 4. The stock market reacts more positively to the announcement of alliances if the increase in the announcing firms' alliance network centrality is greater.

3. Data and Variables

3.1. Alliance network construction

I obtain alliance information from the Thomson Reuters SDC Platinum Joint Venture and Strategic Alliances database (SDC). The SDC provides by far the most comprehensive resource on alliances, including alliances those between public and private corporations and among universities, government agencies, and other types of institutions across a wide range of industries. (Schilling 2009).[6] To focus on the impact of corporate alliances on corporate investment decisions, I impose the following sample selection criteria. First, a deal must include at least two firms in the Compustat/CRSP merged database to focus on interfirm connections via alliances. My sample includes both bilateral alliances and alliances between three or more firms, thereby extending the existing literature, which concentrates on bilateral alliances (Chan, Kensinger, Keown and Martin 1997; Johnson and Houston 2000; Stonitsch 2014).[7] Second, a deal must be announced between 1990 and 2013 because the SDC started systematic data collection only in 1990 (Stonitsch 2014).[8] Third, a deal should not be classified as "rumored" or "intended," which lack public announcements to ensure that I examine actual relations. Overall, my sample includes 16,021 alliance deals between 5,047 unique firms in the Compustat/CRSP merged database.

Panel A of Table 1 summarizes the time-series trend of alliance activities between 1990 and 2013. Column (1) first shows the dramatic surge in alliance activities during the early 1990s. Alliances were at their peak in 1999 and 2000, but experienced a downturn trend afterwards. The

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

[7] Some alliance samples include private firms or nonprofit organizations, which I exclude from the network construction. Since about 93% of alliances in the SDC database are bilateral, this is unlikely to have a substantial impact.

[8] The number of announced alliance deals from SDC increases from 953 in 1989 to 3,318 in 1990. I find no comparable gap in the number of alliances announced between 1988 and 1989, which implies that no systematic trend drives the increase of alliance activities between 1989 and 1990.

severe impact of the financial crisis in the late 2000s on alliance activities is evident in the total number of announced deals in 2009-2011, which is only about the number of deals announced in 2008. The time-series trend is consistent with recent alliance research (König, Liu and Zenou 2014; Schilling 2015). Columns (2) and (3) report that on average, 639 Compustat/CRSP firms (525 U.S. firms) engage in new alliances per year. In addition, the percentage of U.S. firms participating in new alliances per year is 8.69% of all U.S. firms on average (Column 4). Finally, domestic alliances between U.S. public firms are about 61% of my sample alliances, while U.S. firms take accounts for 82% (= 525 / 639) of firms that initiate new alliances per year. Hence, international firms in my sample tend to initiate more alliances per firm.

[Insert Table 1 around here]

Firms can establish various forms of corporate alliances. The SDC classifies alliances into several categories: joint ventures and other contractual agreements such as licensing, manufacturing, marketing, R&D, and technology transfer. Joint ventures establish a separate entity and typically require equity investments from the parent firms.[9] Licensing agreements involve an announcement of licensing and cross-licensing activities for products or technology between partners. Marketing agreements generally indicate a platform to use one firm's distribution networks for the other firms' products and services. R&D agreements pursue joint development of innovative technology and products explicitly. Finally, a technology transfer agreement usually applies when an alliance explicitly indicates the integration or combination of alliance partners' products or knowledge assets. The SDC also provides a brief synopsis for each alliance deal, mostly drawn from the alliance announcement, from which it is possible to find several keywords to determine the alliance categories.

These alliance types are not mutually exclusive since alliance announcements may indicate that some alliance objectives belong to different SDC categories. In this paper, I use all

[9] Joint ventures are often treated as a specific type of corporate partnerships in contrast to other "looser" types of alliances (The Economist 2015). Hagedoorn (2002) documents a decline in joint ventures during the 1990s, but Internet Appendix Table 1 shows that joint ventures grew more popular after the financial crisis in the late 2000s.

types of alliances for three reasons. First, any alliance type can promote knowledge transfer between partners and thus provide a path for information flows (Schilling and Phelps 2007). Second, Powell, Koput and Smith-Doerr (1996) suggest that alliances may target a wider range of activities than those described in alliance announcements, blurring the actual boundaries between alliances types. Finally, I can present a more comprehensive picture of alliance networks that extends the literature, which focuses on R&D alliance networks (König, Liu and Zenou 2014; Schilling 2015; Schilling and Phelps 2007).

Panels B – D of Table 1 summarize the information about the SDC classification of alliance types. First, Panel B shows that 25.62% of the sample alliances are classified into no specific type. They are neither joint ventures nor belong to any other contractual agreement. Of the remaining 74.38%, more than half belong to only one category, while about 5,000 belong to multiple categories. In terms of category distribution, marketing (manufacturing) agreements are the most (least) popular. Next, Panel C shows an interesting pattern in the overlap between alliance types. Specifically, licensing and technology transfer agreements are most likely to overlap, at 40 – 45%, while the likelihood of overlap with joint ventures is less than 10%. R&D agreements have a 36% chance to overlap with technology transfer agreements. In general, manufacturing and marketing agreements tend to overlap with many other types of alliances. Finally, Panel D compares the size of assets, capital expenditure, and R&D expenditure of firms that participate (or not) in each alliance type. Firms engaging in joint ventures are much larger and spend substantially less on R&D on average. On the other hand, licensing, R&D, and technology transfer agreements are more likely to occur between firms operating in R&D-intensive environments. Manufacturing and marketing agreements are in the middle of the distribution.

An alliance network is estimated as a snapshot of ongoing alliances at the end of each calendar year. The SDC rarely reports the date of termination for a given alliance, creating a severe data limitation for measuring the ongoing status of alliances. In fact, only 274 out of 16,021 (1.71%) deals in the 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 and universal length of alliance duration, generally three years (Schilling 2015; Schilling and Phelps 2007) or five (König, Liu and Zenou 2014; Robinson and Stuart 2007) to seven years (König, Liu and Zenou 2014). Most alliances indicate an open-length contract, but a small fraction of alliances specify the expected length. Of the 16,021 deals, 768 (4.79%) report a mean and median "expected" alliance duration of 6.24 years and 5 years, respectively. In addition, the 25th and 75th percentiles of this expected alliance duration are 3 and 7 years, respectively. Hence, I conclude that it is reasonable to use the five-year assumption for alliance duration in the base specification. Moreover, Gomes-Casseres, Hagedoorn and Jaffe (2006) provide evidence that the magnitude of knowledge flows between alliance partners (measured by patent cross-citations) become weaker six years after the beginning of the alliances. Using the five-year assumption, I construct 20 time-varying alliance networks between 1994 and 2013. The time series begin in 1994 because it is the first year for which alliance data exist for the previous five years (1990 – 1994). For example, the alliance network in 1998 is estimated as a collection of alliance connections through alliances announced between 1994 and 1998.

A network includes nodes (participants) and edges (connections), and can be represented as an adjacency matrix in which each matrix element indicates the strength 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. The (i, j) component of the matrix indicates the status of the connection between the i-th and j-th nodes in the network. Following the literature on alliance networks (König, Liu and Zenou 2014; Robinson and Stuart 2007; Schilling and Phelps 2007), I represent an alliance network as an unweighted and undirected adjacency matrix. Each element of the unweighted matrix equals 1 if two nodes are connected and 0 otherwise. Thus, it treats all connections equally. An undirected network matrix imposes a symmetric relationship between nodes. This symmetry assumption is less realistic, but can ensure that all eigenvalues of the matrix are real and help to compute the eigenvector-related centrality measures in the network analysis (Ahern and Harford 2014).

Table 2 summarizes the characteristics of the alliance networks between 1994 and 2013. First, the alliance networks follow a similar time-series trend to the trend of alliance activities in Panel A of Table 1, with a lag of three to five years. For example, Column (1) reports that network size (indicated by the number of nodes) peaks in 2000-2003, while Table 1 shows that the number of announced deals peaks in 1997-2000. Similarly, a sharp decrease in the number of new alliances in 2008-2009 seems to affect network size in 2012-2013. This pattern is natural since the size of an alliance network in one year relies on the intensity of alliance activities during the previous five years. This trend is also comparable to trends reported in recent alliance research (König, Liu and Zenou 2014; Schilling 2015).

[Insert Table 2 around here]

Alliance networks have gradually decentralized during the sample period. Column (3) shows that the mean Degree centrality (the number of direct connections per firm = edges / nodes) is generally decreasing, despite the fluctuation in network size. Consequently, alliance networks have become less clustered. Column (4) further shows this trend: *Clustering Coefficient*, which captures the extent to which a node's neighborhood (directly connected nodes) is also connected each other, is also generally decreasing,

3.2. Network centrality measure

Network centrality is the key variable that captures the position of firms in alliance networks in this paper, thereby proxying the extent of information flows available for firms in the networks. More connected participants are more likely to find their positions in the more central part of a network. For example, Figure 1 illustrates that IBM and Microsoft, which are linked to many other firms via alliances (Table 3), appear in the very central part of their networks. Centrality thus distinguishes more-connected "central" nodes from less-connected "peripheral" nodes.

Prior studies propose several measures of centrality, and all which have unique focuses and limitations. I use Bonacich centrality (Bonacich 1987) to capture the extent of information flows via direct and indirect connections (König, Liu and Zenou 2014; Robinson and Stuart 2007). The Bonacich centrality best fits to this paper's research objectives for two reasons. First, the parameterization provides reliable time-series comparability in centrality values. Alliance networks substantially fluctuate in their size and density (Figure 1). Thus, the measure conforms well to the standard investment regressions with firm fixed effects focusing on the impact of within-firm variation in determinants of investment decisions. Second, I can decompose Bonacich centrality into direct and indirect connections through networks. Thus, I can design a test that controls for the impact of direct alliance connections largely related to endogeneity concerns in alliance formation decision.

Consider a network consisting of n nodes. 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 discounting factor for the impact of indirect connections – an indirect connection works at a probability of β in each trial of information transmission. β must be sufficiently small to ensure a well-defined measure, because the measure is the sum of all direct and indirect connections to which a node can reach through the network via *all* possible paths. For a well-defined measure, any parametrization of Bonacich centrality preserves the ordinal ranking of centrality within a network. Appendix 2 provides more detail on the construction of Bonacich centrality.

While the choice of α and β might be arbitrary, existing studies suggest a guideline to the choice of parameters. I choose parameters to measure the *absolute* importance of nodes. Specifically, each direct connection has the same value and I discount each indirect connection at the same rate, regardless of network size and density. The intuition is as follows. Notice that an isolated single pair of nodes (two nodes connect only to each other) must be the least connected nodes in any networks. To the extent that they engage in no new alliances, other connections available in the networks will not affect their isolated connection. Capturing the absolute importance of nodes implies that these nodes will have the same, minimum value of centrality in any alliance network. To achieve this objective, I first obtain the plausible range for β following Robinson and Stuart (2007): β is set to three-quarters of the reciprocal of the largest eigenvalue of $\boldsymbol{G}$. I represent the 20 networks 20 different adjacency matrices, thereby generating 20 estimated values of β. My analysis suggests that the β between 0.01 and 0.03 will produce a stable value of Bonacich centrality in *any* of 20 the networks. Therefore, I use 0.02 as my base parameter value of β. For a robustness check, I also run tests using 0.01 and 0.03 and show similar results (Section 4.6). It is worth noting that even a change of 0.01 in the value of β largely increases or decreases the value of centrality (Table A2 of Appendix 2) since the measure considers *all* possible paths of information flows. Finally, I choose α such that the minimum value of centrality always equals unity, thus setting the value of each direct connection to 1.[10]

Columns (5) – (9) of Table 2 report the summary statistics of Bonacich centrality. First, the decrease in the mean value of Bonacich centrality is consistent with the decentralization in alliance networks (Columns 3 and 4 of Table 2). Thus, the measure design effectively captures the changes in the size and density of networks. The minimum value of Bonacich centrality is always 1 by construction, indicating that two nodes in an isolated single pair are always assigned a fixed minimum value. Additionally, Columns (8) and (9) suggest that the measure is highly right-skewed, which can distort the estimates in linear specifications. Following Ahern (2013), I take the natural logarithm of Bonacich centrality, *Log(Centrality),* for the regressions.

Table 3 lists the changes in the top 25 central U.S. public firms during the sample period. Since my alliance networks largely overlap in a short horizon, Table 3 reports the alliance network centrality ranking for six selected years to show the distinct changes in the list of key firms. Several giant firms in the networks such as IBM, Microsoft, HP, GE, GM, and AT&T are easy to identify. Given their importance in the U.S. economy, it is unsurprising to find these firms among the most central in alliance networks. Moreover, the list includes several firms operating in the media and entertainment sectors, such as News Corp, Time Warner, and Walt Disney. Thus, my alliance networks capture alliance activities between firms in a wide range of industries, thereby extending the literature, which generally focuses on manufacturing sectors (König, Liu and Zenou 2014; Schilling and Phelps 2007).

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[10] Robinson and Stuart (2007) choose α such that $\boldsymbol{C}'\boldsymbol{C} = n$. This parametrization scales the measure of centrality upward for small networks, which is inconsistent with the decentralization shown in Section 3.1.

[Insert Table 3 around here]

3.3. Descriptive statistics

I use an unbalanced panel of U.S. public firms in alliance networks to isolate the impact of the country-specific characteristics of international firms cross-listed in the U.S. stock market. I exclude financial (SIC 6000–6999) and utility (SIC 4900–4999) firms due to the strong regulations on these industries. Sample firms should have at least $10 million (in 2009 dollars) of assets (*at*) and non-missing values of Tobin's Q ([*at* – *ceq* + *prcc_f* * *csho*] / *at*) and capital expenditure (*capx*). I also restrict the sample to firms with at least 30 daily stock return observations to compute a firm-specific return variation as a proxy for the private information contained in stock prices (Section 4.2). My final sample consists of 18,830 firm-year observations between 1994 and 2013.

Table 4 provides the descriptive statistics for the variables used in the empirical tests. All but indicator and log-transformed variables are winsorized at the 1st and 99th percentiles to avoid distortion due to extreme outliers. The sample mean (median) value of *Log(Centrality)* is 1.158 (0.854). To understand the importance of indirect connections on the value of Bonacich centrality, I also present the summary statistics of *Log(Degree)*, the natural logarithm of degree centrality equal to the number of direct connections. The sample mean (median) value of *Log(Degree)* is 0.745 (0.693), which is 36% (19%) lower than the mean (median) value of *Log(Centrality)*. Since Bonacich centrality counts all possible paths of information flows through the networks, a small chance of communication through indirect connections (β: base value equals 2%) generates noticeable increases in the volume of information flows compared to an analysis that considers only direct connections.

[Insert Table 4 around here]

Regarding investment measures, the mean and median values of *CAPEX* are 6.0% and 3.8%, respectively, while the mean and median values of *CAPEX* + *R&D* are 15.2% and 10.5%, respectively. On average, *R&D* has more importance in our sample firms' investment than *CAPEX*, though about 25% of the firm-year observations report missing *R&D* items in Compustat. This difference becomes even greater for a sub-sample of 13,647 firms with non-missing *R&D*: the mean value of *R&D* is 12.6% while that of *CAPEX* is 5.4% (= 0.180 – 0.126). In sum, the sample firms show a pattern that indicates the increasing importance of *R&D* in total investment, consistent with Brown and Petersen (2009) and Peters and Taylor (2017).

Panel B presents the correlation coefficient table between *Log(Centrality)* and other key variables in the regressions. First, *Log(Centrality)* is positively correlated with both *CAPEX* and *R&D*, suggesting that firms more centrally located in alliance networks tend to invest more. Additionally, *Log(Centrality)* is positively correlated with *Log(Assets)* and *Log(Age)*, implying that bigger and mature firms are more likely to be central in alliance networks. The positive correlation between *Log(Centrality)* and Tobin's Q indicates that growth firms tend to be more central. On the other hand, *Log(Centrality)* is negatively correlated with leverage, which is consistent with the fact that the highly central firms in Table 3 are mostly operating in high-tech industries that use less debt. Finally, the stock prices of more central firms are less likely to be informative and these firms are more likely to be diversified (Section 4.2 describes the variables).

4. Does Alliance Network Centrality Reduce the Investment-to-Price Sensitivity?

4.1. Baseline results

To test whether the investment of more centrally located firms is less sensitive to their own stock prices, I estimate the following OLS regression model:

$$\begin{aligned} I_{i,t} = {} & \beta_1 Log(Centrality)_{i,t-1} + \beta_2 Log(Centrality)_{i,t-1} Q_{i,t-1} + \beta_3 Q_{i,t-1} \\ & + \beta_4 Log(Centrality)_{i,t-1} CF_{i,t-1} + \beta_5 CF_{i,t-1} + \boldsymbol{\Gamma} \times \boldsymbol{X}_{i,t-1} + \alpha_i + \tau_t + \epsilon_{i,t} \end{aligned} \tag{2}$$

where $I_{i,t}$ is the measure of investment of firm *i* in year *t*. I use the following measures of corporate investment: capital expenditure (*CAPEX*: *capx*) to proxy for tangible capital investment, research and development expenditure (*R&D: xrd*) to proxy for intangible capital investment, and the sum of *CAPEX* and *R&D* (*CAPEX* + *R&D*) to capture total capital investment. $I_{i,t}$ is scaled by the beginning value of assets.[11] $Log(Centrality)_{i,t-1}$ is the natural logarithm of the Bonacich centrality of firm i in year $t-1$. $Q_{i,t-1}$ proxies for the price-based investment opportunities of firm i in year $t-1$. $CF_{i,t-1}$ is the cash flow (*ib* + *dp* + *xrd*) of firm i in year $t-1$, and included in the regression to control for its impact on corporate investment (Fazzari, Hubbard and Petersen 1988). I add R&D expenditures to cash flows as they are mostly expensed rather than capitalized under U.S. accounting practices (Brown and Petersen 2009; Chen, Goldstein and Jiang 2007). My baseline regression controls for the beginning value of assets, *Log(Assets)*, since firm size may capture additional aspects of investment capacity (Foucault and Fresard 2014; Foucault and Frésard 2012). Finally, calendar year (τ_t) and firm (α_i) fixed effects control for any unobservable constant time- and firm-specific heterogeneity.[12]

The coefficient of interest is β_2, which shows the impact of alliance network centrality on investment-to-price sensitivity. I predict a negative and statistically significant β_2 (*Hypothesis 1*). To control for the channels through which alliance network centrality may directly affect corporate investment, I include *Log(Centrality)* in the regression. I have no specific prediction on the sign of the coefficient on *Log(Centrality)* (β_1), since the actual investment *level* will depend on whether the information from alliance networks indicates positive or negative prospects about future investment opportunities. I also include the interaction term between *Log(Centrality)* and *CF* to isolate the financing channel through which alliance network centrality can affect investment (β_4). Moreover, cash flows are a non-price based measure of investment opportunities (Edmans, Jayaraman and Schneemeier 2016). Therefore, a positive or insignificant interaction term between *Log(Centrality)* and *CF* in the opposite direction of my prediction for the interaction term between *Log(Centrality)* and *Q* can bolster my argument that alliance network centrality

[11] Following Chen, Goldstein and Jiang (2007), I normalize investment measures by total assets instead of physical capital (in general, property, plant and equipment) because my sample contains some non-manufacturing firms relying less on physical assets.

[12] My findings are similar when I replace firm fixed effects with industry-year fixed effects (Internet Appendix Table 2). This result is consistent with Roberts and Whited (2013) who suggest that including firm fixed effects is less likely to produce materially different results for a regression in which the dependent variables are already first-differenced, such as corporate investment.

reduces managers' need to learn from stock prices rather than the sensitivity of investment to a more general measure of investment opportunities.

Table 5 reports the baseline results. First, Column (1) shows that the coefficient on *Log(Centrality)* × *Q* is negative and statistically significant at the 1% level. This finding is consistent with the first hypothesis that more central firms in alliance networks rely less on the information contained in stock prices for making future investment decisions. On the other hand, the coefficient on *Log(Centrality)* × *CF* is positive and insignificant. Thus, alliance network centrality shows no significant influence on investment-to-cash flow sensitivity and does not reduce the sensitivity of investment to non-price based measure of investment opportunities. Regarding the other variables, both Tobin's Q and cash flows (*CF*) positively predict the amount of future investment, which is consistent with findings from the vast literature on corporate investment.

[Insert Table 5 around here]

I further investigate the impact of alliance network centrality on the sensitivity of intangible capital investment to stock prices, either as a part of total capital investments (Columns 2 and 3: *CAPEX* + *R&D*) or as a standalone measure of investment (Column 4: *R&D*). Using *R&D* as a dependent variable needs careful attention because firms may strategically choose not to report an *R&D* item in their financial statements. Given the greater importance of *R&D* than *CAPEX* in the sample firms (Table 4), it is important to examine the influence of missing *R&D* firms. I use two approaches. In Column (2), I set the missing *R&D* items to zero, following many prior studies, particularly when R&D is an independent variable. In Columns (3) and (4), I exclude the missing *R&D* firms from the regression sample, without filling in a zero for missing *R&D* firms when *R&D* is a standalone dependent variable. The takeaway from Columns (2) – (4) is that the coefficients on *Log(Centrality)* × *Q* are all negative and statistically significant at the 1% level, suggesting a negative and significant impact of alliance network centrality on both intangible and total investment-to-price sensitivity.

The economic significance of my findings can be calculated as follows. Table 4 shows that *Log(Centrality)* at the 25th percentile of the sample distribution is 0.101, while *Log(Centrality)* at the

75th percentile is 1.859. This difference corresponds to 1.54 standard deviations of *Log(Centrality).* Using the estimated coefficients from the regression of *CAPEX* in Column (1) of Table 5, the investment-to-price sensitivity of "central" firms (at the 75th percentile) is 0.180 less (= 0.117 × 1.54) than that of "peripheral" firms (at the 25th percentile). This reduction corresponds to 17% of the baseline sensitivity of investment to Tobin's Q (β_3 = 1.048) for the least connected firms in their networks (*Log(Centrality)* = 0). A similar calculation shows a reduction in the investment-to-price sensitivity from central to peripheral firms by 16% (*CAPEX* + *R&D* in Column 2), 22% (non-missing *CAPEX* + *R&D* in Column 3), and 24% (non-missing *R&D* in Column 4).

4.2. Alternative explanations

In this section, I address the concern that alliance network centrality can proxy for firm characteristics other than the informational advantages that networks provide. First, Table 3 shows that the most central U.S. public firms in alliance networks tend to be large and old with a greater visibility. Thus, alliance network centrality may indicate a dearth of private information contained in stock prices, since these firms tend to operate in a rich informational environment with a significant amount of public information. In this case, alliance network centrality will negatively affect the investment-to-price sensitivity because managers learn less from stock prices (Chen, Goldstein and Jiang 2007), regardless of the information flows through alliance networks. To isolate the impact of the volume of private information in stock prices, I add the measure of private information contained in stock prices and their interaction terms with Tobin's Q in the regression. First, following Chen, Goldstein and Jiang (2007) and Foucault and Fresard (2014), I use firm-specific return variation as a proxy for the informativeness of stock prices (Durnev, Morck and Yeung 2004; Foucault and Fresard 2014):

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

where R^2 is the R-squared from the regression of daily individual stock returns on the daily returns of value-weighted market and industry (SIC 3-digit) portfolios. I require at least 30 observations of daily returns each calendar year to compute *Informativeness* (Chen, Goldstein and

Jiang 2007). Second, I use the probability of informed trading (*PIN*) as a proxy for the private information contained in stock prices. I obtain the *PIN* dataset used in Brown and Hillegeist (2007) from Stephen Brown's website (available until 2010).[13]

Alliance network centrality can also proxy for the extent of corporate diversification. Chen, Goldstein and Jiang (2007) find that more diversified firms' investments are less sensitive to price-based investment opportunities because the market may have less ability to evaluate the operation of diversified firms compared to focused firms. Robinson (2008) shows that alliances are more likely to occur in diversified businesses than in core businesses since they often pursue a risky project with uncertain outcomes but greater upside potentials. Thus, firms with a higher alliance network centrality are more likely to be diversified, which can lead to a lower investment-to-price sensitivity, regardless of the information flows from alliance networks. To rule out the channel of corporate diversification, I include a measure of corporate diversification, *Diversification*, and its interaction term with Tobin's Q in the regression, following Chen, Goldstein and Jiang (2007). *Diversification* is one minus the Herfindahl-Hirschman Index of the SIC 4-digit business segment sales reported in the Compustat historical segment database.

Table 6 reports the estimation results after including additional control variables related to the volume of private information contained in stock prices and the extent of corporate diversification. Consistent with Chen, Goldstein and Jiang (2007), I find that the interaction terms between Tobin's Q and both *Informativeness* and *PIN* positively predict future investment, except for Column (1), where I estimate the impact of *Informativeness* on the sensitivity of *CAPEX* to Tobin's Q. For other investment measures, both *Informativeness* and *PIN* show a statistically significant and positive impact on the investment-to-price sensitivity at the 1 – 5% level. These alternative explanations do have explanatory powers, thereby reducing the magnitude and statistical significance of the findings, particularly regarding R&D investment. However, more importantly, the coefficient on *Log(Centrality)* × *Q* is still negative and statistically significant in six of eight columns. Even in Columns (7) and (8), where non-missing *R&D* is the dependent

[13] I thank Stephen Brown for making the PIN dataset publicly available.

variable, the coefficient is negative and very close to statistically significance (t-stats are -1.64 and -1.63). These results suggest that the negative impact of alliance network centrality on investment-to-price sensitivity is not driven simply by the volume of private information contained in stock prices or the extent of diversification.[14]

[Insert Table 6 around here]

Foucault and Fresard (2014) show that managers learn more (less) from other information resources such as product market competitors' stock prices when their own stock prices are less (more) informative. This finding implies that the informational impact of alliance networks on investment-to-price sensitivity might be weaker if managers can extract more information from their own stock prices. To test this argument, I use a controlled experiment based on the SEC's Regulation SHO that includes a pilot program that decreases the cost of short selling for an arbitrarily chosen group of Russell 3000 index stocks.[15] Fang, Huang and Karpoff (2016) show that the pilot program improves price efficiency of selected stocks. Thus, the negative relation between alliance network centrality and investment-to-price sensitivity may decrease for these pilot stocks because managers have less incentives to learn from alliance networks.

Following Fang, Huang and Karpoff (2016), I estimate the following Difference-in-Differences regression on the sensitivity of investment to Tobin's Q:

$$\begin{aligned} I_{i,t} = {} & \beta_1 \times Q_{i,t-1} + \beta_2 \times Q_{i,t-1} \times Pilot + \beta_3 \times Q_{i,t-1} \times During + \beta_4 \times Q_{i,t-1} \times Pilot \times During \\ & + \beta_5 \times Pilot + \beta_6 \times During + \beta_7 \times Pilot \times During + \beta_8 CF_{i,t-1} + \boldsymbol{\Gamma} \times \boldsymbol{X}_{i,t-1} \\ & + \alpha_i + \tau_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

[14] As a robustness check, I also examine the results after including the natural log of the number of following analysts in year $t-1$, *Log(Analyst)*, and its interaction term with Tobin's Q in the regressions with or without stock price informativeness. I do not include analysts-related variables in my main tests because their economic channels overlap with *Informativeness* or *PIN*. My findings remain similar, except for the regression with non-missing R&D as a standalone dependent variable, which shows a negative but insignificant coefficient (t-stats are around -0.9 to -1.3). I report these results in Internet Appendix Table 3.

[15] I thank Vivian Fang for generously providing me with the CRSP PERMNO-matched dataset of Russell 3000 index firms with an indicator variable of pilot stocks.

where *Pilot* is an indicator variable that equals 1 if the firm belongs to the pilot stocks and 0 otherwise. *During* is an indicator variable that equals 1 if the observation is drawn from the experiment period (2005 – 2007) and 0 otherwise (2001 – 2003). The year of implementation (2004) is excluded. β_4 measures the treatment effect of pilot program on investment-to-price sensitivity. Year and firm fixed effects are included to control for the time-invariant firm-level heterogeneity in the level of investment. Sample firms should have at least four observations of Bonacich centrality during these six years, which reduces the sample size for this test to 3,352 firm-year observations.

However, the goal of this test is not examining the impact of experiment on investment-to-price sensitivity *per se*. Rather, I need to test the impact of alliance network centrality on the coefficient on the triple-interacted term (β_4). Unfortunately, it is almost impossible to interpret quadrupole interaction terms that involves alliance network centrality as an additional layer of interaction. Instead, I divide the sample firms into two groups: *Central* and *Non-central* based on the median value of Bonacich centrality, which is calculated by the average of centrality across all pre- and during-experiment periods (2001 – 2003 and 2005 – 2007). I expect β_4 is more positive and stronger for *Central* than *Non-central* firms since the reversal impact of increase in stock price efficiency should be greater for more central firms.

Table 7 reports the estimation results. In all specifications, the estimated coefficients on $Q \times Pilot \times During$ are all positive and significant in *Central* sub-sample, but negative or insignificant in *Non-central* sub-sample. This adverse impact of stock price efficiency on the network effect is consistent with the informational implication of alliance networks, which suggests that managers may have less incentives to learn from alliance networks when they can extract more information from their own stock prices.

[Insert Table 7 around here]

4.3. The impact of financial constraints

My main results show that more central firms in alliance networks rely less on stock prices for making future investment decisions since they have better access to alternative sources of information about new investment opportunities. However, existing studies provide evidence that financially constrained firms might lack the ability to immediately respond to new investment opportunities due to frictions in financial markets (Fazzari, Hubbard and Petersen 1988). Therefore, it is interesting to investigate whether firms' financial constraints also affect the impact of alliance network centrality on investment-to-price sensitivity. Chen, Goldstein and Jiang (2007) find that the positive impact of stock price informativeness on investment-to-price sensitivity is stronger for large firms than small firms. They interpret the results as evidence that large firms are less likely to be financially constrained and have a better ability to immediately incorporate new information from the stock market into their investment decisions. Similarly, central but financially *constrained* firms might be less able to exploit their informational advantages from alliance networks. In sum, I predict that the negative impact of alliance network centrality on investment-to-price sensitivity will be stronger for financially unconstrained firms (*Hypothesis 2*).

To test this hypothesis, I first conduct a sub-sample test with some proxies for financial constraints. In this paper, I use three different measures of financial constraints. First, large firms are less likely to be financially constrained due to having better experience and reputation, which can help them secure external financing from financial markets more easily. I use *Firm Size* (measured by total assets) as a measure of financial constraints, following Almeida and Campello (2007), Bakke and Whited (2010), and Edmans, Jayaraman and Schneemeier (2016). Second, Almeida and Campello (2007) argue that firms with available bond ratings are more likely to have easier access to financial markets because the ratings provide investors with an external validation of the firms' financial status. I create an indicator variable *Bond Rating* equal to 1 if firms have either short- or long-term bond ratings from Standard and Poor's (S&P) available in Compustat, and 0 otherwise. I exclude firms with zero leverage from this sub-sample construction. Finally, I use a popular measure of financial constraints, the WW Index (Whited and Wu 2006), defined as: – 0.091 × *CF* – 0.062 × *Dividend Payer Dummy* + 0.021 × *Long-term Debt* – 0.044 × *Log(Assets)* + 0.102 × *Industry Sales Growth (SIC 3-digit)* – 0.035 × *Firm Sales Growth*. Appendix 1 provides detailed definitions of the variables.

Using the three measures of financial constraints, I construct a sub-sample of financially unconstrained and constrained firms. I double-sort the sample firms to balance the variation in alliance network centrality within each sub-sample since centrality and the measures of financial constraints are correlated: positively for *Firm Size* and negatively for *WW Index*.[16] Specifically, I first divide the sample firms into two groups by above and below the median value of the Bonacich centrality, and then further divide firms into two groups by above and below the median value of each measure of financial constraints within each centrality group. I then combine the financially constrained (unconstrained) group from each centrally group into a sub-sample of financially constrained (unconstrained) firms. The balance of centrality variation between two sub-samples largely improve after double-sorting.

Table 8 reports the estimation results using double-sorted sub-samples based on the three measures of financial constraints: *Firm Size, Bond Rating*, and *WW Index*. For brevity, I report only the coefficient of interest, *Log(Centrality)* × *Q* (see Internet Appendix Table 4 for the full coefficients). In all columns, the magnitude and statistical significance of the coefficients are greater for the group of financially unconstrained firms: large firms, firms with a bond rating, and firms with a low *WW Index*. Moreover, all estimated coefficients in the group of financially constrained firms (Columns 2, 4, 6, and 8) are statistically insignificant with *t*-stats close to zero. The estimated coefficients in Column (7) in which non-missing *R&D* is the dependent variable are still negative but insignificant for large firms and firms with a bond rating, while their *t*-stats are close to significance (-1.51 for both). The coefficient in Column (7) for firms with a low *WW Index* is negative and statistically significant at the 5% level. Overall, the findings show that central and financially *unconstrained* firms can better exploit the informational advantages from alliance networks.

Next, I examine the impact of exogenous changes in firms' financial constraints using the 2007-2008 financial crisis. Specifically, I identify the impact of short-term debt maturing at the onset of financial crisis on the relation between alliance network centrality and investment-to-

[16] Since *Bond Rating* is an indicator variable, I do not double-sort the variable.

price sensitivity. Following Almeida, Campello, Laranjeira and Weisbenner (2012) and Kini, Shenoy and Subramaniam (2017), I first restrict the sample to firms with fiscal year-end dates between July 2007 and January 2008. The key variable is *DD1Due* equal to the proportion of long-term debt maturing in one year after the fiscal year-end dates (*dd1*) over total amount of long-term debt (*dd1* + *dltt*). This variable measures the financial pressure due to debt maturing on the onset of financial crisis. Importantly, the shock is less likely to be anticipated when debt contracts were made. The sample size reduces to 512 because the sample only includes one observation per firm with non-missing value of Bonacich centrality.

To test the impact of an exogenous shock on firms' financial constraints due to the financial crisis, I estimate the following OLS regression models:

$$\begin{aligned} I_{i,t} = \beta_1 Log(Centrality)_{i,t-1} + \beta_2 Log(Centrality)_{i,t-1} Q_{i,t-1} \\ + \beta_3 Log(Centrality)_{i,t-1} Q_{i,t-1} DD1Due \\ + \beta_4 Log(Centrality)_{i,t-1} DD1Due + \beta_5 Q_{i,t-1} DD1Due + \beta_6 DD1Due \\ + \beta_7 Q_{i,t-1} + \beta_8 Log(Centrality)_{i,t-1} CF_{i,t-1} + \beta_9 CF_{i,t-1} + \Gamma \times X_{i,t-1} + \epsilon_{i,t} \end{aligned} \quad (5)$$

where the coefficient of interest is β_3 that measures the additional effect of *DD1Due* on the relationship between alliance network centrality and investment-to-price sensitivity. I expect a positive coefficient of β_3 that indicates a weaker relation between alliance network centrality and investment-to-price sensitivity.

Table 9 summarizes the estimated coefficients. Consistent with the prediction, β_3 is always positive and significant at the 5% level in three of four regressions. Hence, the results further provide evidence that financial constraints limit firms' ability to exploit the informational advantages from alliance networks.

[Insert Table 9 around here]

4.4. Identification strategy

My main results report OLS estimates on the impact of alliance network centrality on investment-to-price sensitivity. However, these estimates can be biased due to the endogenous nature of alliance formation decision that affects alliance network centrality. Specifically, alliance formation can be endogenously determined with other corporate policies such as investment and financing decisions. There are two layers of alliance formation decision. First, some latent factors may affect both the decision of engaging in new alliances in addition to existing alliances and corporate investment policies (omitted variables). Second, some firms may never enter alliance networks, or enter the networks in one time and exit in another time. Therefore, I can observe the relation between alliance network centrality and investment-to-prices sensitivity only for firms in the networks (self-selection). This section addresses these omitted variables and self-selection issues. First, I control for the influence of the initiation of new alliances using quasi-exogenous changes in alliance network centrality due to changes in indirect connections through alliance networks. Second, I use a state-level variation in corporate income reporting requirement to investigate the concern of self-selection into alliance networks.

4.4.1. Exogenous changes in centrality due to changes in indirect connections

The purpose of this section is to control for the influence of the initiation of new alliances. I use two approaches. My first set of tests follows the method used in Anjos and Fracassi (2015). Specifically, changes in alliance network centrality consist of three distinct parts: (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. Firm fixed effects can control for time-invariant firm-level heterogeneity, and thus largely reduces the endogeneity concern on (i). I have little concern about (iii) since it is unlikely for a single firm to engage in alliances to alter the structure of entire alliance networks. Thus, (ii) is most likely affected by the firms' endogenous alliance formation decision. In my empirical setting, changes in centrality due to the termination of existing alliances are less problematic, since the alliance networks are built on an assumption that all alliances universally terminate after five years.[17] In sum, the initiation of alliances is the most severe identification in this paper.

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 year of my alliance networks, the first firm-cohort "Firm-1994" is defined by the alliance announced in 1993. "Firm-1994" continues until 1995 because the firm initiates no alliances in 1995. Then, "Firm-1994" is replaced by a new firm-cohort in 1996, namely "Firm-1996", as the firm initiates a new alliance in 1996. By the same token, "Firm-1996" is replaced by a new firm-cohort in 1997 ("Firm-1997") that continues until 2000. The final firm-cohort will be "Firm-2001" in the above example, and last for five years until 2005 based on the five-year assumption of alliance duration.

Using the series of firm-cohorts defined at the firm-year level, I include firm-cohort fixed effects in the regressions. The firm-cohort fixed effects largely control for the changes in centrality due to the initiation of alliances, since any observable effects of alliance network centrality in firm-year observations with new alliances will be absorbed by the firm-cohort fixed effects. Moreover, the firm-cohort fixed effects control for (i) above, because they are subsets of the firm fixed effects. In sum, any remaining observable effects of alliance network centrality can be attributed to (iii) the changes in centrality due to changes in overall network structure, which are less likely driven from the endogenous alliance formation decision.

Columns (1) – (4) of Table 10 report the estimation results using the firm-cohort fixed effects instead of firm fixed effects. Other regression specifications are the same as earlier, but I exclude the interaction term between alliance network centrality and cash flows (*Log(Centrality)* × *CF*) because there is no prior reason to believe that the changes in information flows due to overall network structure changes will affect investment-to-cash flow sensitivity. The coefficients on *Log(Centrality)* × *Q* are all negative but only significant at the 10% level in Columns (3) and (4). These weaker results can be explained by two factors. First, direct connections should have much

[17] Section 4.6 shows that my findings are robust to different assumptions on alliance duration.

greater impacts on investment-to-price sensitivity, which is intuitive and incorporated in the design of measure. My base specification assumes that each indirect connection has a chance of 2% (β in the Bonacich centrality) per each trial of information transmission. Second, using the firm-cohort fixed effects only rely on the within-firm variation in alliance network centrality for firms that do not regularly engage in new alliances, and thus creates a considerably restrictive testing environment. Specifically, the number of firm-cohort fixed effects is about 2.5 times the number of firm fixed effects: 8,460 vs. 3,303 (Columns 1 and 2) and 6,296 vs. 2,417 (Columns 3 and 4). Many frequent initiators of alliance (on an annual basis or even more frequently), including the most central firms in alliance networks such as IBM or Microsoft, can provide very little contributions to the power of test because their changes in centrality are likely to be absorbed by the firm-cohort fixed effects.

[Insert Table 10 around here]

My second test follows Larcker, So and Wang (2013), which also relies on the changes in indirect connections through networks. Bonacich centrality is the sum of both direct and indirect connections with discounts. I can decompose it into two mutually exclusive parts of centrality: direct and indirect connections. Since I set the strength of each direct connection to 1, the sum of direct connections is equivalent to degree centrality. Thus, I define a measure of indirect part of centrality, *Indirect*, as the difference between Bonacich and degree centrality. Finally, I add one to *Indirect* centrality to retain samples with no indirect connections. In sum, I test the impact of *Indirect* centrality on investment-to-price sensitivity, controlling for the impact of *Degree* centrality (= direct connections).

I focus on a sub-sample of firms that (i) engage in no new alliances, and (ii) experience no changes in degree centrality. Thus, any changes in Bonacich centrality of this sub-sample of firms should be driven by the changes in indirect connections. A negative and significant impact of the *Indirect* centrality on investment-to-price sensitivity can alleviate the endogeneity concern in the alliance formation decision. Columns (5) – (8) of Table 10 report the estimation results. The sample size reduces to 8,346 (Columns 5 and 6) and 5,827 (Columns 7 and 8). Regression specifications include the firm fixed effects, thereby relying on the within-firm variation in *Indirect* centrality. Still, the coefficients on *Log(Indirect + 1)* × *Q* are always negative, though they are only statistically significant at the 5% level in Column (5) and the 10% level in Column (6).

Overall, Table 10 provides some evidence that the impact of alliance network centrality on the investment-to-price sensitivity are not entirely driven by the endogenous decision of alliance participation that affects alliance network centrality.

4.4.2. Self-selection: state-level variation in corporate income reporting requirement

There is a self-selection issue that only some firms voluntarily participate in alliances. Other firms never participate in alliances, or enter and then exit from time to time. To address the self-selection issue, I estimate a Heckman model with the two-step estimator (Heckman 1979) in which the first stage estimates a model for the likelihood of participating in alliance networks and the second stage tests the impact of alliance network centrality on investment-to-price sensitivity.

In the selection stage of regressions, I exploit a state-level variation in corporate income reporting requirement as an instrument for the decision of engaging in alliance networks, following Bodnaruk, Massa and Simonov (2013). Many U.S. firms operate in multiple states, and each state has different income reporting requirement. More than one third of U.S. states adopt combined reporting rule that treats the parent and subsidiaries of corporations as a single entity for state income tax purposes (Mazerov 2009).[18] On the other hand, separate reporting rule requires each subsidiary (including the parent) to report income to the state in which it operates. Combined reporting rule has become more popular as it can nullify the tax benefit from income-shifting from states with high tax rates to states with low tax rates or tax-haven states. For example, many firms have established a subsidiary in the State of Delaware that holds trademarks that generate a substantial amount of loyalty income (Mazerov 2009). Bodnaruk, Massa and Simonov (2013) argue that combined reporting rule reduces the cost of engaging in alliances. According to Robinson (2008) that views strategic alliances as a commitment technology to execute new risky projects, forming alliances is an alternative to internal project execution. Thus, combined

[18] Appendix 3 summarizes the list of states that have adopted combined reporting requirements.

reporting rule reduces the tax benefit from internal transactions (between parent and subsidiaries), thereby increasing the relative benefit of forming alliances. In sum, firms operating more intense in states with combined reporting requirement are more likely to engage in alliances.

To calculate a firm-level index of combined reporting requirement, I use the dataset of geographic footprint of U.S. public firms, which is constructed by García and Norli (2012).[19] This dataset contains firm-level geographic dispersion of operating activities by parsing 10-K or equivalent documents from U.S. Securities and Exchange Commission (SEC) EDGAR database. Specifically, the dataset includes firm-level identifiers and provides firm-state-year level scores that measure the intensity of operations. Using the included Compustat identifiers, I match the dataset to the state-level adoption status of combined reporting requirement (Appendix 3) to assign a weight of 1 or 0 that is determined by whether each state has adopted combined reporting requirement by the year of index construction. Finally, I aggregate the firm-state-year level scores at the firm-year level by computing a weighted average with the weight described above. This index variable is called *Combined Reporting*. I begin with 65,412 firm-year observations between 1994 and 2013 in Compustat/CRSP merged database that meet my sample selection criteria (Section 3.3). As the geographic footprint dataset is only available until 2008, my final sample size reduces to 38,255 in the first stage and 13,252 in the second stage.[20]

Table 11 reports the estimation results of Heckman model. Specifically, the dependent variable in the first stage is an indicator variable of whether a firm is a member of the alliance network in year t (Columns 1 and 4). To be consistent with regression specifications in previous sections, I include *Q*, *CF*, *Log(Assets)*, *Price Informativeness, Price Informativeness* × *Q, Diversification,*

[19] I appreciate Diego Garcia and Oyvind Norli for making the dataset publicly available.

[20] I also use two variations of firm-level index of combined reporting requirement. First, I use the historical headquarter information from S&P Capital IQ and construct a binary version of firm-level index, which is limited to capture operating activities outside headquartered states. Second, I use the original dataset of Bodnaruk, Massa and Simonov (2013) that contains the information about corporate subsidiaries from Dun and Bradstreet. This dataset spans on the period between 1998 and 2004, thereby substantially reducing sample size (I do not extrapolate the scores before and after). Using these variations produces very similar results to Table 9, which are reported in Internet Appendix Table 6. I appreciate Andriy Bodnaruk for generously sharing the dataset.

and *Diversification* × *Q* as predictors of participating into alliance networks. I also include year and industry (SIC 3-digit) dummy variables.[21] First, *Combined Reporting* positively predicts the selection decision with a statistical significance at the 1% level. More importantly, in the outcome regression (Columns 2, 3, 5 and 6), the coefficients on *Log(Centrality)* × *Q* are all negative and statistically significant at the 1% level. The coefficients on the inverse Mills ratio are statistically significant at the 1% level (except for the regressions predicting *CAPEX*), which suggests a presence of selection bias in the relation between alliance and investment decisions. In sum, Table 11 shows that the negative impact of alliance network centrality on investment-to-price sensitivity is less likely to be affected by the self-selection into alliance networks.

[Insert Table 11 around here]

4.5. Alliance types: R&D vs. Non-R&D alliances

My baseline results make no distinction between alliance types, since all types of alliances share a feature specialized in knowledge transfer between alliance partners (Schilling and Phelps 2007). However, there is a substantial heterogeneity in organizational forms and activities across alliances. Many studies in the alliance literature exclusively focus on the networks of R&D-related alliances (König, Liu and Zenou 2014; Schilling 2015; Schilling and Phelps 2007), because alliances are often pursued for risky projects (Robinson 2008) that typically involve joint research or mutual exchange of technology (Schilling 2009). Table 1 shows that licensing, R&D, and technology transfer agreements are likely to occur between firms operating in an R&D-intensive environment (R&D-related alliances), while joint ventures, marketing, and manufacturing agreements are more popular in less R&D-intensive environments. Intuitively, R&D-related alliances are likely to convey useful information about *R&D*, and thus affect negatively on the sensitivity of *R&D* to stock prices rather than the sensitivity of *CAPEX*. In this section, I test the above prediction.

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[21] I do not include firm dummies in the Probit model of selection equation as the model generally does not converge. Even at the SIC 3-digit level of industry dummies, I exclude the observations from SIC 3-digit industries that the industry classification perfectly predicts the selection decision (i.e. no variation in alliance decisions within the same SIC 3-digit industry). Otherwise, the model generally does not converge.

I divide my sample alliances into two groups: *R&D Alliance* and *Non-R&D Alliance*. Based on the discussion in Section 3.1 and statistics shown in Panel D of Table 1, the group of *R&D Alliance* includes licensing, R&D, and technology transfer agreements. On the other hand, the group of *Non-R&D Alliance* includes joint ventures, manufacturing, and marketing agreements, after excluding alliance that belong to *R&D Alliance*.[22] Then, I separately construct an alliance network and calculate Bonacich centrality for each group of alliances: *Bonacich R&D* and *Bonacich Non-R&D*. Panel A of Table 4 shows that the size of two sub-networks are comparable: *R&D Alliance* networks produce 10,475 firm-year observations, while *Non-R&D Alliance* networks produce 9,964 observations. Finally, I compute *R&D Alliance Ratio* defined as the ratio of *Bonacich R&D* to the sum of *Bonacich R&D* and *Bonacich Non-R&D*. For firms with a missing centrality in only one sub-network, I set the centrality in that sub-network to zero. However, I exclude firms only participating in alliances that report no specific types (i.e., missing centrality in both sub-networks). Two sub-samples are constructed by above and below the median value of *R&D Alliance Ratio*: *High* and *Low*. The median value of *R&D Alliance Ratio* is 0.567.

Table 12 examines whether the impact of alliance network centrality on R&D investment-to-price sensitivity is stronger for firms in the *High R&D Alliance Ratio* group. The dependent variable is non-missing *R&D* in Columns (1) and (2). The coefficients on *Log(Centrality)* × *Q* are negative in both models, but only significant in *High* group (Column 1). As related tests, Columns (3) and (4) further examine whether the impact of alliance network centrality on the *CAPEX* investment-to-price sensitivity is stronger for firms in the *Low R&D Alliance Ratio* group. The coefficients on *Log(Centrality)* × *Q* are negative in both models, but only significant in *Low* group (Column 4). Thus, the results generally support my prediction on differential impacts of different types of alliances on investment-to-prices sensitivity. Nevertheless, the differences in the magnitude and statistical significance of coefficients between two groups seem immaterial. A possible explanation is that actual alliance activities might reach beyond those announced at the beginning of alliances, which can blur the boundary between alliance types reported in the SDC.

[22] Alliances that report no specific types are excluded from this analysis.

[Insert Table 12 around here]

4.6. Robustness tests

This section tests the robustness of my findings to a variety of regression and network specifications as well as network centrality measures. The dependent variable is *CAPEX* (Column 1), *CAPEX + R&D* (Column 2), and *CAPEX + R&D* (Column 3) or *R&D* (Column 4) of firms reporting non-missing items. For brevity, I only report the coefficient of interest, *Log(Centrality)* × *Q* in Table 13. Full coefficients are reported in Internet Appendix Table 7.

[Insert Table 13 around here]

First, I investigate the robustness of my findings to alternative specifications of investment regressions. Existing studies on the investment regression with Tobin's Q show that the estimated OLS coefficients suffer from measurement errors because Tobin's Q is only able to imperfectly measure true but unobservable firm-level investment opportunities (Erickson and Whited 2000; Erickson and Whited 2002). Hence, I use the cumulant estimator of Erickson, Jiang and Whited (2014) that provides unbiased estimates of coefficients in errors-in-variables panel regressions (a STATA module *xtewreg* is available). Specification (1) estimates the baseline regression (Equation 2) using the third-order cumulant estimator that specifies two mismeasured regressors: Tobin's Q and its interaction term with *Log(Centrality)*. The estimated coefficients on *Log(Centrality)* × *Q* are negative and statistically significant.

I also use two alternative measures of price-based investment opportunities. Specification (2) uses *Total Q* developed by Peters and Taylor (2017) that capitalizes R&D and a portion of selling, general, and administrative expenses (SG&A) as a part of total capital to measure price-based investment opportunities, which seems a better proxy for investment opportunities. Specification (2) uses *Industry Q* defined as a value-weighted average of Tobin's Q at the SIC 3-digit industry level. Both Q measures generate negative and statistically significant coefficients.

It is possible that the negative impact of alliance network centrality on investment-to-price sensitivity may capture some non-linearity in the relationship between corporate investment and

Tobin's Q. For example, if corporate investment is concave in Q and more centrally located firms in alliance networks tend to have higher Q, then the investment of firms with a higher alliance network centrality will be less sensitive to Q. In fact, the correlation between *Log(Centrality)* and Q is positive (0.086 from Panel B of Table 4). To address this concern, Specification (4) controls for the squared term of Q, following Baker, Stein and Wurgler (2003) and Chen, Goldstein and Jiang (2007). The coefficients on *Log(Centrality)* × *Q* are still negative and statistically significant in all regression models.

Specification (5) additionally controls for a set of firm characteristics that potentially affect future investment decisions: firm age, sales growth, leverage, and cash holding. This choice of variables follows Asker, Farre-Mensa and Ljungqvist (2015) and Edmans, Jayaraman and Schneemeier (2016). Some of these variables may proxy for investment opportunities or financial constraints that are not captured by Tobin's Q and cash flows. Internet Appendix Table 7 shows that the estimated coefficients on these variables are generally significant, particularly for firm age and leverage which are negatively associated with the investment. However, my findings are very similar after the inclusion of these additional controls.

In Specification (6), I exclude firms from the sample if they report more than 20% changes in their total assets, as these firms might be undergoing material changes in their operations such as mergers or delisting.[23] Specification (7) estimates Fama-MacBeth regressions (Fama and MacBeth 1973) to investigate cross-sectional differences in the impact of alliance network centrality on investment-to-price sensitivity. Still, the estimated coefficients are negative in all regression models, and statistically significant in most of them.

Specifications (8) – (11) use alternative specifications of alliance networks to check the robustness of my results. First, my base specification assumes the five-year duration for all alliances (Section 3.1). Hence, I also use two alternative assumptions: three and seven years. Specifications (8) and (9) show that my findings are robust to different assumptions of alliance duration. Second, there might be a concern about a potential bias in my findings due to some

[23] The results are similar for alternative cutoff values: 15% or 25%.

systematic differences between domestic and international alliance deals, as my sample only includes U.S. domestic while it counts on the alliance connections between domestic and international firms. I test the potential influence of this choice in two different ways. Particularly, Specification (10) constructs alliance networks that only consist of domestic deals that involve at least two U.S. public firms. On the other hand, Specification (11) constructs alliance networks that consist of entire global alliance deals involving not only firms but also universities, government agencies, and other institutions. Regardless of alliance network specifications, the estimated coefficients are negative in all regression models, and statistically significant in most of them.

Finally, I examine the sensitivity of my results to a variety of network centrality measures (Specifications 12 – 16). First, I investigate alternative parameter choices in the calculation of Bonacich centrality. My base parameter value for β is 0.02 (Section 2.2), which determines the strength of indirect connections in information trasnmission. 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 use 0.01 and 0.03 as alternative choices of parameter values: "Bonacich-" and "Bonacich+". I also use the degree centrality that equals the number of direct connections, which is identical to the Bonacich centrality with a zero β. Specifications (12) – (14) report the estimation results using Bonacich-, Bonacich+, and degree centrality. An interesting pattern emerges as the impact of alliance network centrality on investment-to-price sensitivity is likely to be stronger for centrality measures that assign greater values on the chance of information transmission per each indirect connection (0%, 1% and 3% for degree, Bonacich- and Bonacich+). Therefore, ignoring indirect connections through alliance networks seemingly underestimates the informational advantages from firms in the networks. More importantly, the estimated coefficients are always negative, and statistically significant in most of regression models.

Second, I use two other popular measures of centrality: eigenvector and betweenness centrality (See Appendix 2 for more detail on network centrality measures). First, the eigenvector centrality is similar to Bonacich centrality in the sense that both measures consider indirect connections to determine network centrality. Eigenvector centrality is more efficient in static or stable networks such as industry-level input-output networks (Ahern and Harford 2014), whereas Bonacich centrality provides more measurement flexibility with parametrization for scaling and discount factors. On the other hand, betweenness centrality represents the extent that a node stands like a gate for the information flows through networks. It is higher when the node is in the middle of "shortest paths" between many other nodes. 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.[24] Specifications (15) and (16) use eigenvector and betweenness centrality to test the impact of alliance network centrality on investment-to-price sensitivity. Still, the takeaway from these tests is that the coefficients on *Log(Centrality)* × *Q* are always negative, and statistically significant in most of regression models.

5. Do Alliance Networks Convey Valuable Information?

5.1. Market value regression

This paper documents a negative and statistically significant impact of alliance network centrally on investment-to-price sensitivity, which can be explained by that alliance networks are conduits of useful and publicly unavailable information about future investment opportunities. Thus, more central firms possess informational advantages vis-à-vis peripheral firms in alliance networks. In this section, I test whether these informational advantages are value-enhancing using panel regressions and event study analysis. If the informational advantages from alliance networks are value-enhancing, alliance network centrality will be positively associated with firm value (*Hypothesis 3*) as more central firms should have better ability to select value-increasing projects. On top of that, the informational benefit from forming a new alliance will be greater if

[24] Appendix 2 reports positive correlations (0.36 – 0.52) between the betweenness other centrality measures.

the new alliance further increases the announcing firm's alliance network centrality. Hence, I predict a positive relation between alliance announcement wealth effects and the magnitude of increase in alliance network centrality due to the new alliance (*Hypothesis 4*).

First, to test *Hypothesis 3*, I estimate the following OLS regression model:

$$Q_{i,t} = \alpha + \beta \times Log(Centrality)_{i,t-1} + \boldsymbol{\Gamma} \times \boldsymbol{X}_{i,t-1} + \epsilon_{i,t} \quad (6)$$

where $Q_{i,t}$ is Tobin's Q of firm i in year t, $Log(Centrality)_{i,t-1}$ is the natural logarithm of the Bonacich centrality of firm i in year $t-1$, and $\boldsymbol{X}_{i,t}$ is a vector of control variables in year $t-1$. Following the previous literature such as Bebchuk, Cohen and Ferrell (2009), I control for *Log(Assets)*, *Log(Age)*, *ROA*, *PPE*, *R&D*, *CAPEX*, leverage, and stock return volatility measured as a standard deviation of daily returns. I also include calendar year and firm fixed effects.

Table 14 presents the estimation results. Column (1) shows a positive but insignificant (t-stats = 1.20) coefficient on *Log(Centrality)*. Hence, I delve into a sub-sample test using some proxies for financial constraints since Table 8 shows that the impact of alliance network centrality on investment-to-price sensitivity is stronger for financially unconstrained firms. Using the same three measures (*Firm Size*, *Bond Rating*, and *WW Index*), Columns (2) – (7) show that the impact of alliance network centrality on Tobin's Q is positive and statistically significant at the 1 – 5% level for financially unconstrained firms, but negative and insignificant for financially constrained firms. Hence, this result is also consistent with the previous finding that central and financially *unconstrained* firms in alliance networks may have better ability to exploit their informational advantages from alliance networks.

[Insert Table 14 around here]

5.2. Value responses to industry-specific shocks

Alliance networks can be conduits for conveying information such as technology-related knowledge, product or geographic market prospects, human capital, and more general economic conditions that help detecting future investment opportunities. As an alternative angle of value-implication of alliance networks, I test whether the informational advantages from alliance networks enable more central firms to better anticipate future industry conditions. Dass, Kini, Nanda, Onal and Wang (2014) argue that directors from related industries help firms predict future industry prospects more accurately. They find that the effect of industry-specific shocks on firm value is more positive for firms with a presence of those directors from related industries. Similarly, I investigate whether the value responses to industry-specific shocks are more positive for firms with a higher alliance network centrality.

To measure industry-specific shocks, I follow Harford (2005) and extract the first principal component of seven variables that proxy for industry status: asset turnover, capital expenditure, employee growth, net profit margin, R&D expenditure, return on assets, and sales growth. I use the median value of variables from each year and industry (SIC 3-digit) to estimate the principal component: *Industry Shock Index*.

I estimate the following OLS regression model:

$$\Delta Q_{i,t} = \alpha + \beta_0 Log(Centrality)_{i,t-1} + \beta_1 Log(Centrality)_{i,t-1} Industry\ Shock\ Index_{i,t} + \beta_2 Industry\ Shock\ Index_{i,t} + \boldsymbol{\Gamma} \times \boldsymbol{X}_{i,t-1} + \epsilon_{i,t} \quad (7)$$

where $\Delta Q_{i,t}$ is the change in Tobin's Q of firm *i* between year t – 1 and t. $Log(Centrality)_{i,t-1}$ is the natural logarithm of the Bonacich centrality of firm *i* in year t – 1. *Industry Shock Index* is measured at year t to test whether the informational advantages from alliance networks help firms anticipate future industry conditions more accurately. $\boldsymbol{X}_{i,t-1}$ is a vector of control variables measured at year t – 1, including *Log(Assets)*, *Log(Age)*, *ROA*, *PPE*, *R&D*, *CAPEX*, leverage, and stock return volatility as well as calendar year and firm fixed effects. The coefficient of interest is β_1 that captures the impact of informational advantages from alliance networks on the value responses to industry-specific shocks. It is also worth noting that β_2, which captures the impact of *Industry Shock Index* on firm value, is expected to be positive.

Firms can benefit more from the informational advantages from alliance networks in extreme circumstances where industries are undergoing substantially positive or negative shocks. To examine this argument, I create an indicator variable *Positive (Negative) Industry Shock* equal to

1 if *Industry Shock Index* belongs to the top (bottom) 10th percentile of the index distributions. I then estimate the following OLS regression model:

$$
\begin{aligned}
\Delta Q_{i,t} = \alpha + \beta_0 Log(Centrality)_{i,t-1} + \beta_1 Log(Centrality)_{i,t-1} Positive\ Industry\ Shock_{i,t} \quad (8) \\
+ \beta_2 Positive\ Industry\ Shock_{i,t} \\
+ \beta_3 Log(Bonacich)_{i,t-1} Negative\ Industry\ Shock_{i,t} \\
+ \beta_4 Negative\ Industry\ Shock_{i,t} + \boldsymbol{\Gamma} \times \boldsymbol{X}_{i,t-1} + \epsilon_{i,t}
\end{aligned}
$$

where variable definitions are identical to those in Equation (7). The coefficients of interest are β_1 and β_3 that estimate the impact of informational advantages from alliance networks on the value responses to extremely positive and negative industry shocks. It is also worth noting that β_2 (β_4) that captures the impact of *Positive Industry Shock* (*Negative Industry Shock*) on firm value is expected to be positive (negative).

Notice that *Industry Shock Index* is an exogenous shock from the perspective of firms, and thus reduce the endogeneity concern in the OLS regression. Nevertheless, to further alleviate the endogeneity concern in the endogenous nature of alliance formation decision, I also present the estimation results where the firm fixed effects are replaced by the firm-cohort fixed effects that exploit the within-firm variation in alliance network centrality of firm-year observations without an initiation of alliances (Section 4.4.1).

Table 15 reports the test results. In Columns (1) and (2), the coefficients on *Log(Centrality)* × *Industry Shock Index* are positive and statistically significant at the 5% level. Thus, firms more centrally located in alliance networks better anticipate future industry conditions on average, suggested by more positive value responses to industry-specific shocks. Interestingly, alliance network centrality asymmetrically affects the value responses to positive and negative industry shocks. Specifically, in Columns (3) and (4), the estimated coefficients on *Log(Centrality)* × *Positive Industry Shock* are positive and statistically significant at the 5 – 10% level, while the estimated coefficients on *Log(Centrality)* × *Negative Industry Shock* are negative (significant at the 10% level in Column 4). A possible explanation is that more central firms in alliance networks are more likely to face the transmission of micro-level shocks though alliance connections, consistent with

Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012) who propose a similar idea in input-output networks. In fact, Boone and Ivanov (2012) find that the non-bankrupt strategic alliance partners experience negative stock returns around their partner firm's bankruptcy filing announcement. When industries possess many growth options, however, the informational advantages from alliance networks help more central firms detect new investment opportunities and make better investment decisions.

[Insert Table 15 around here]

5.3. Alliance announcement effects

In this section, I test whether the stock market reacts more positively to the announcement of alliances if the new alliance more largely increases the announcing firm's alliance network centrality, reflecting the greater informational benefits from the new alliance (*Hypothesis 4*). Additionally, I test whether alliances between more central firms are expected to create greater synergies using their informational advantages, which leads to more positive combined wealth effects around the period of alliance announcements.

I calculate the increase in the Bonacich centrality due to new alliances as follows:

$$\Delta Centrality_t = 1 + Partner\ Centrality_{t-1} \times \beta \tag{9}$$

where *Partner Centrality* is Bonacich centrality of partner firm measured at the previous year of alliance announcement. β is the discounting factor of parameter in the calculation of Bonacich centrality, with a base value of 0.02. In this setting, the increase in Bonacich centrality due to new alliances is defined as the sum of new direct connection (= 1) and all new indirect connections through the partner firm (*Partner Centrality* × 0.02). Notice that this definition is unable to fully estimate the changes in existing indirect connections *not* via new alliances (e.g. one of current alliance partner of announcing firm has been allied with the new partner firm). Measuring this change is computationally cumbersome since the alliance networks are estimated as a snapshot at the calendar year-level, rather than at the announcement-level. However, my definition of the increase in Bonacich centrality still provides a good approximation, because the magnitude of indirect connections is relatively small and thus unlikely to be the first-order factor of centrality increases.

The event study sample consists of alliances between firms with non-missing alliance network centrality in the previous year of announcements. Since the alliance networks span on the period between 1994 and 2013, the event study sample is drawn from alliances announced between 1995 and 2013. Following the existing literature (Bodnaruk, Massa and Simonov 2013; Chan, Kensinger, Keown and Martin 1997; Stonitsch 2014), I restrict the sample to bilateral alliances between two U.S. public firms. Cumulative abnormal returns (*CAR*) are estimated in a three-day window (-1, 1) using market-adjusted returns (CRSP value-weighted index).[25] *CAR* is winsorized at the 1st and 99th percentiles to reduce the effect of extreme outliers.

Table 16 provides descriptive statistics of variables used in the event study analysis. First, the stock market positively reacts to the announcement of alliances on average. The mean and median value of three-day *CAR* are 0.959% and 0.176%, respectively. This positive market reaction is consistent with the existing literature (Chan, Kensinger, Keown and Martin 1997; Johnson and Houston 2000; McConnell and Nantell 1985). On the other hand, the sign of wealth effects at the alliance-level is mixed on average. The mean and median value of three-day *Combined CAR* are 0.128% and -0.024%, and the mean and median value of three-day *Combined Dollar Gain* are 8.001 and -1.490 million dollars, respectively.

[Insert Table 16 around here]

To test whether a greater increase in centrality due to new alliances leads to higher announcement effects, I estimate the following OLS regression models:

$$CAR_{i,t} = \alpha + \beta_1 \times Log(Centrality)_{i,t-1} + \beta_2 \times Log(\Delta Centrality)_{i,t} + \boldsymbol{\Gamma} \times \boldsymbol{X}_{i,t-1} + \epsilon_{i,t} \qquad (9)$$

[25] My findings remain qualitatively similar when I use a two-day event window (-1, 0) as well as market-model in which parameters are estimated within the window (-239, 6). These results are reported in the Internet Appendix Table 8.

where $CAR_{i,t}$ is the cumulative abnormal returns for firm i around the alliance announcement in year t. Cumulative abnormal returns (*CAR*) are estimated in a three-day window (-1, 1) using market-adjusted returns (CRSP value-weighted index).[26] The main independent variable is $Log(\Delta Centrality)_{i,t}$ that measures the increase in Bonacich centrality due to new alliances. I include $Log(Centrality)_{i,t-1}$ in the regression to control for the current extent of informational advantages from alliance networks. $\boldsymbol{X}_{i,t-1}$ is a vector of additional control variables in year $t-1$, including the firm's market capital measured at 50 trading days before the alliance announcement (*Market Capital*) and alliance types (*R&D Alliance* and *Non-R&D Alliance*). Chan, Kensinger, Keown and Martin (1997) observe greater wealth effects from horizontal alliances than non-horizontal alliances. Thus, I also include an indicator variable equal to 1 if alliances are formed between firms operating in the same SIC 3-digit industry, and 0 otherwise (*Horizontal Alliance*). In some specifications, I control for additional firm characteristics including *ROA*, *Cash Holding*, and *Leverage*. Finally, calendar year and industry (SIC 2-digit level) fixed effects are included in the regression to control for unobservable time- and industry-specific factors.

Table 17 shows the impact of increase in alliance network centrality due to new alliances on the firm-level announcement wealth effects. In all specifications, the estimated coefficients on *Log(ΔCentrality)* are positive and significant at the 1% level, thereby showing that the market positively evaluates the informational benefit from connecting to firms more centrally located in alliance networks. It is also worth noting that the estimated coefficients on *Log(Centrality)* are positive and significant at the 5-10% level, consistent with the idea that more central firms have a better ability to select value-enhancing projects.

[Insert Table 17 around here]

Next, to examine whether the stock market expects greater synergies from alliances between more central firms in alliance networks, I estimate the following OLS regression models:

[26] Internet Appendix Table 9 shows that my results remain very similar when I use a two-day event window (-1, 0) as well as market-model in which parameters are estimated within the window (-239, 6).

$$Combined\ CAR\ (\text{or}\ Combined\ Dollar\ Gain)_{i,t} = \alpha + \beta \times Both\ Central (\text{or}\ Combined\ Centrality\ )_{i,t-1} + \boldsymbol{\Gamma} \times \boldsymbol{X}_{i,t-1} + \epsilon_{i,t} \quad (8)$$

where $CAR_{i,t}$ is the cumulative abnormal returns for firm *i* around an alliance announcement in year t. *Combined CAR* is calculated at the alliance-level by taking a value-weighted average, where the weight is determined by each firm's market capital measured 50 trading days before the announcement. *Combined Dollar Gain* is the sum of firms' dollar wealth gain calculated as *CAR* multiplied by each firm's market capital at the beginning of the 3-day event period. The main independent variable is *Both Central* that is an indicator variable equal to 1 if both firms' centrality values are above the median of the centrality distribution within the event study sample, and 0 otherwise. As an alternative specification, I also use a continuous version of combined centrality variable: *Combined Centrality* is the sum of firms' Bonacich centrality measured in the previous year of announcement. $\boldsymbol{X}_{i,t-1}$ is a vector of control variables in year t – 1, including the sum of two firms' market capital measured 50 trading days before the announcement (*Combined Market Capital*) and alliance types (*R&D Alliance*, *Non-R&D Alliance,* and *Horizontal Alliance*). Finally, calendar year fixed effects are included to control for unobservable time-specific factors.

Table 18 shows the impact of combined alliance network centrality on combined wealth effects around alliance announcements. Columns (1) and (3) estimate the impact on *Combined CAR*, and Columns (2) and (4) estimate the impact on *Combined Dollar Gain*. First, the estimated coefficients on *Both Central* are positive and significant at the 1% level, thereby showing that the market expects greater synergies from alliances between firms already central in alliance networks. Specifically, if both firms are central, three-day *Combined CAR* is 0.613% higher, and three-day *Combined Dollar Gain* is 565 million dollars greater. On the other hand, the coefficients on *One Central* are positive but statistically insignificant. Turning to the continuous version of combined centrality variable, Column (3) shows a positive and statistically significant impact of *Combined Centrality* on *Combined CAR*. However, the impact of *Combined Centrality* on *Combined Dollar Gain* is insignificant with *t*-stats close to zero (Column 4). A possible explanation is that this continuous version of combined centrality variable is limited to distinguish the expected synergies from alliances between firms both central or one central and the other peripheral.

Overall, the results show that the market reacts more positively to the alliance announcements when both firms possess greater informational advantages from alliance networks.

[Insert Table 18 around here]

For other variables in the regression, *Combined Market Capital* is negatively associated with combined wealth effects. Also, consistent with the finding of Chan, Kensinger, Keown and Martin (1997) *Horizontal Alliance* is positively related with combined wealth effects, though the coefficients are not statistically significant. Finally, no significant association is observed between combined wealth effects and types of alliances measured by *R&D Alliance* and *Non-R&D Alliance*, compared to the base group of alliances that report no specific types.

6. Conclusion

This paper performs a large-scale network analysis to study the impact of corporate alliances on corporate investment decision and valuation. One important benefit of participating in alliances is the organizational structure specialized in information sharing and knowledge transfer between partners. I characterize a network of alliances as a conduit for conveying useful and publicly unavailable information about future investment opportunities. I empirically construct time-varying alliance networks and calculate network centrality that captures the idea that more connected firms tend to find their location in more central part of networks. Hence, firms with a higher alliance network centrality can possess informational advantages in detecting future investment opportunities. My research objective is to examine whether alliance network centrality affects corporate investment policies, when the influence of centrality becomes stronger, and how the centrality is related to firm valuation.

My main hypothesis predicts that the investment of firms with a higher alliance network centrality is less sensitive to Tobin's Q that proxies for price-based investment opportunities, since managers may rely less on the information contained in stock prices for making investment decisions. Supporting this hypothesis, alliance network centrality negatively affects investment-to-price sensitivity. The investment of central (at the 75th percentile of the centrality distribution) firms is 15 – 20% less sensitive to Tobin's Q than that of non-central firms (at the 25th percentile). The negative relation between alliance network centrality and investment-to-price sensitivity becomes insignificant for financially constrained firms, suggesting that financial constraints may limit firms' ability to exploit the informational advantages from alliance networks. To address the endogeneity concern in alliance formation decision, I show that quasi-exogenous changes in alliance network centrality due to changes in the indirect connections via alliance partner firms also negatively affect the sensitivity of investment to Tobin's Q. My findings are not fully driven by several alternative explanations and self-selection issues into alliance networks. Finally, the results are robust to a variety of regressions and network specifications as well as measures of network centrality.

Alliance network centrality is positively related to firm value (measured by Tobin's Q) on average. In addition, firms more centrally located in alliance networks better anticipate future industry conditions, suggested by the more positive value responses when facing industry-specific shocks. Moreover, I find a positive relation between the magnitude of increase in centrality from new alliance and the announcement wealth effects, consistent with the prediction that the stock market positively evaluates the better access to the information resources of more central firms via alliance networks. There is also a higher value creation for alliances between firms already central in alliance networks, suggesting that the market expects greater synergies using these firms' greater informational advantages.

This paper has three main contributions to the finance literature. First, the evidence from this paper characterizes alliances as a channel for learning new information that affects corporate investment decisions, thus adding to the existing literature on the role of alliances in information sharing and knowledge transfer between partners. Second, this paper fits into the recently growing literature on the informational role of financial markets in corporate investment decisions. Specifically, I show that the information flows through alliance networks can reduce the sensitivity of investment to price-based investment opportunities. Finally, I contribute to the literature on network analysis application in financial economics. This paper is the first to present a comprehensive picture of time-varying alliance networks to analyze their informational impacts on specific corporate policies. Moreover, this paper highlights the benefit of using Bonacich centrality to handle substantial time-series variations in network characteristics and endogeneity concerns in the decision of network participation.

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Table 1
Characteristics of Sample Alliance Deals

This table summarizes the characteristics of sample alliance deals. The sample consists of 16,021 alliance deals announced in 1990-2013 and formed between at least two firms in Compustat/CRSP merged (CCM) database. Panel A presents the number of announced deals (Column 1), the number of CCM firms in alliance deals Column (2), the number of U.S. CCM firms in alliance deals (Column 3), the ratio of U.S. CCM firms in alliance deals to total U.S. CCM firms (Column 4), and the proportion of domestic (Column 5) and international deals (Column 6). Panel B reports the number of alliance deals classified into none, single, multiple categories, and each of categories defined by SDC. Panel C summarizes the frequency of combinations of different alliance types. Panel D compares firm size and investments of firms participating in each alliance type.

Panel A: Alliance Trends

Year	Deals Announced	All Firms	U.S. Firms	U.S. Firms with New Alliances / Total U.S. CCM Firms (%)	Domestic Deals (%)	International Deals (%)
	(1)	(2)	(3)	(4)	(5)	(6)
1990	509	473	403	6.91	60.12	39.88
1991	826	639	549	9.18	67.31	32.69
1992	1,003	759	676	10.72	72.68	27.32
1993	1,025	819	713	10.18	68.78	31.22
1994	1,136	930	809	11.01	65.67	34.33
1995	1,141	1,044	890	11.92	70.90	29.10
1996	868	887	770	9.76	72.93	17.07
1997	1,227	1,132	966	12.29	69.85	30.16
1998	1,229	1,145	950	12.71	64.28	35.72
1999	1,447	1,228	1,045	14.45	68.90	31.10
2000	1,272	1,000	776	11.24	48.19	51.81
2001	768	704	530	8.48	46.75	53.26
2002	499	561	417	7.09	51.50	48.50
2003	543	625	783	13.90	55.80	44.20
2004	409	516	387	6.89	54.77	45.23
2005	458	558	452	8.15	61.57	38.43
2006	391	472	385	7.06	60.87	39.13
2007	360	484	374	6.98	62.22	37.78
2008	278	365	273	5.41	54.68	45.32
2009	115	171	119	2.49	53.04	46.96
2010	72	122	84	1.82	47.22	52.78
2011	134	211	173	3.82	65.67	34.33
2012	181	265	216	4.85	63.54	36.46
2013	130	214	168	3.72	62.31	37.69
Total	16,021	639	525	8.69	61.23	38.77

Panel B: SDC Classification of Alliance Types		
SDC Classification	Obs.	% Obs.
No Category	4,105	25.62
Single Category	6,831	42.64
Multiple Categories	5,175	32.30
2	*3,474*	*21.68*
3	*1,254*	*7.83*
4+	*447*	*2.79*
Total	16,021	100.00

SDC Categories	Obs.	% Obs. (over 11,916 = Alliances Classified into Any of Categories)
Joint Venture	3,391	28.46
Licensing Agreement	2,992	25.11
Manufacturing Agreement	2,111	17.72
Marketing Agreement	4,358	36.57
R&D Agreement	3,253	27.30
Technology Transfer	3,288	27.59

Panel C: Overlap of Alliance Types								
		% of Alliances Types Overlap: Column / Row Obs.						
Category	Obs.	Single	J.V.	Licensing	Manufacturing	Marketing	R&D	Tech.
Joint Venture	3,391	60.54	.	1.62	20.50	15.10	11.21	7.96
Licensing	2,992	27.37	1.84	.	15.37	27.77	19.02	49.23
Manufacturing	2,111	22.07	32.92	21.79	.	32.88	22.55	44.20
Marketing	4,358	45.20	15.74	19.07	15.92	.	25.15	22.60
R&D	3,253	31.02	11.68	17.49	14.63	33.69	.	36.64
Tech. Transfer	3,288	15.63	8.21	44.80	28.38	29.96	36.25	.

Panel D: Characteristics of Firms Announcing Alliances by Alliance Types								
Firms in Alliance Types	Participating				Not Participating			
Category	Obs.	Assets ($B)	CAPEX (%)	R&D (%)	Obs.	Assets ($B)	CAPEX (%)	R&D (%)
Joint Venture	4,963	58.03	7.08	3.21	14,549	23.76	6.08	11.04
Licensing Agreement	5,119	17.52	6.01	13.41	14,393	37.80	6.45	7.50
Manufacturing Agreement	3,168	29.64	6.51	8.51	16,344	33.03	6.30	9.15
Marketing Agreement	7,350	24.77	6.22	9.37	12,162	37.14	6.41	8.90
R&D Agreement	5,537	23.98	6.51	13.23	13,975	35.84	6.27	7.39
Tech. Transfer	5,565	21.28	6.46	11.95	13,947	36.95	6.29	7.89
Any of Categories	19,512	32.48	6.33	9.05	6,266	45.71	5.75	5.85

Table 2

Characteristics of Alliance Networks and Bonacich Centrality

This table reports the statistics for alliance networks and Bonacich centrality 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 average number of direct connections per node, which equals the ratio of *Edges* to *Nodes*. *Clustering Coefficient* is the average ratio of a node's existing connections to all possible connections between its directly connected nodes. The next four columns provide summary statistics for Bonacich centrality. See Appendix 2 for details on the definition and construction of Bonacich Centrality.

	Network				Bonacich Centrality				
Year	Nodes	Edges	Degree	Clustering Coefficient	Mean	Median	Min	Max	Skewness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1994	1,753	8,576	4.89	0.281	11.13	3.41	1	372.21	6.02
1995	1,988	9,398	4.73	0.265	10.97	3.26	1	381.57	6.29
1996	2,108	9,802	4.65	0.267	10.87	3.33	1	400.28	6.61
1997	2,297	10,166	4.43	0.240	9.71	3.14	1	369.52	6.98
1998	2,369	10,134	4.28	0.212	8.68	2.96	1	323.87	7.16
1999	2,445	10,030	4.10	0.196	8.25	2.73	1	323.81	7.82
2000	2,354	10,322	4.38	0.213	9.15	3.08	1	344.72	7.42
2001	2,151	9,690	4.50	0.197	9.24	3.09	1	339.93	7.26
2002	1,973	8,648	4.38	0.188	8.36	3.00	1	296.31	7.08
2003	1,789	7,826	4.37	0.183	7.73	2.74	1	246.89	6.79
2004	1,571	6,454	4.11	0.192	6.35	2.45	1	187.69	6.54
2005	1,433	4,634	3.23	0.135	4.23	2.02	1	116.36	6.66
2006	1,312	3,782	2.88	0.101	3.55	2.00	1	93.17	6.76
2007	1,270	3,536	2.78	0.097	3.35	1.88	1	85.24	6.53
2008	1,167	3,040	2.60	0.094	3.07	1.44	1	72.33	6.36
2009	1,036	2,552	2.46	0.100	2.85	1.27	1	58.49	5.78
2010	840	1,996	2.38	0.100	2.68	1.21	1	45.97	5.19
2011	742	1,642	2.21	0.103	2.45	1.15	1	33.59	4.73
2012	655	1,478	2.26	0.186	2.48	1.16	1	26.47	3.56
2013	599	1,254	2.09	0.220	2.25	1.09	1	17.46	2.97
Mean	1,593	6,248	3.59	0.192	6.37	2.32	1	206.79	8.19

Table 3

Alliance Network Centrality Ranking Between 1994 and 2013

This table lists the top 25 central U.S. public firms (non-financial and non-utility) 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	Comcast
3	HP	HP	AOL Time Warner	Motorola	IBM	Microsoft
4	Digital Equipment	AT&T	HP	Sun Microsystems	Yahoo	Anadarko Petro.
5	Motorola	Motorola	Sun Microsystems	Intel	Intel	AT&T
6	Apple	AOL	Oracle	GE	Google	News Corp.
7	GE	Sun Microsystems	GE	HP	HP	Exxon Mobil
8	Microsoft	Intel	Lucent Tech.	Cisco	Time Warner	Yahoo
9	Novell	Compaq	Cisco	Merck & Co	Motorola	Google
10	Sun Microsystems	Oracle	AT&T	Yahoo	Oracle	EMC
11	Oracle	Apple	Intel	EMC	News Corp.	Johnson & Johnson
12	GM	Novell	Motorola	Disney	CBS	Chevron
13	Intel	GE	GM	Applera Corp.	EMC	Disney
14	Texas Instruments	Unisys	3Com	Comcast	AT&T	Pfizer
15	DuPont	Texas Instruments	EDS	Oracle	Comcast	Intel
16	Bellsouth	GM	Ford	CBS	Honeywell	Apache
17	Tandem Computers	Eastman Kodak	Yahoo	Johnson & Johnson	Johnson & Johnson	Enterprise Products
18	Bell Atlantic	Cisco	RealNetworks	Time Warner	Verizon	Chesapeake
19	Compaq	Bell Atlantic	Siebel Systems	DuPont	Adobe	IBM
20	Silicon Graphics	DuPont	Eastman Kodak	Ebay	Qualcomm	Qualcomm
21	GTE	Lucent Tech.	I2 Tech.	Abbott Lab.	ConocoPhillips	Verizon
22	Eastman Kodak	Adobe	Ariba	Sprint Nextel	United Tech.	Merck & Co
23	US West Inc.	GTE	Dell	Ford	Cisco	Time Warner Cable
24	National Semicon.	Silicon Graphics	Commerce One	First Data	Bristol-Myers	Time Warner
25	NYNEX	Qualcomm	SBC Comm.	RealNetworks	Viacom	Cablevision

Table 4

Descriptive Statistics

Panel A presents the summary statistics for variables used in the regressions. My sample consists of 18,830 U.S. firm-year observations in alliance networks between 1994 and 2013. See Appendix 1 for the complete list of variable definitions. All variables are winsorized at the 1st and 99th percentiles, except for network centrality measures (*Bonacich* and *Degree*), *Assets*, *Age*, *Price Informativeness*, *PIN*, *Diversification*, *Bond Rating*, *Combined Reporting (HQ)*, and *Industry Shock Index*. Panel B shows the correlation coefficients between *Log(Centrality)* and a host of variables used in the empirical tests.

Panel A: Summary Statistics

	N	Mean	Std.	P25	Median	P75
Network Centrality Measures						
Log(Centrality)	18,830	1.158	1.141	0.101	0.854	1.859
Log(Degree)	18,830	0.745	0.930	0	0.693	1.099
Log(Bonacich R&D)	10,475	0.786	0.911	0.035	0.533	1.242
Log(Bonacich Non-R&D)	9,964	0.545	0.746	0	0.122	0.809
Dependent Variables						
CAPEX	18,830	0.060	0.072	0.019	0.038	0.073
CAPEX + R&D	18,830	0.152	0.150	0.051	0.105	0.201
CAPEX + R&D (non-missing)	13,647	0.180	0.160	0.073	0.131	0.230
R&D (non-missing)	13,647	0.126	0.145	0.024	0.082	0.172
Other Variables						
Assets ($ billion)	18,830	7.243	31.656	0.117	0.564	3.335
Age (years)	18,830	19.944	16.025	8	13	28
Q	18,830	2.385	1.839	1.265	1.748	2.755
CF	18,830	0.083	0.178	0.038	0.104	0.177
Price Informativeness	18,830	1.586	2.124	0.340	1.530	2.894
PIN	17,325	0.163	0.085	0.104	0.147	0.207
Diversification	18,830	0.127	0.219	0	0	0.204
Leverage	18,830	0.202	0.204	0.012	0.161	0.316
Cash Holding	18,830	0.243	0.246	0.039	0.150	0.390
Sales Growth	18,830	0.274	0.822	-0.017	0.097	0.272
Asset Growth	18,830	0.133	0.440	-0.060	0.051	0.194
PPE	18,830	0.227	0.206	0.074	0.155	0.311
Return Volatility	18,830	0.038	0.021	0.022	0.034	0.049
Total Q	18,830	1.744	2.705	0.428	0.895	1.842
Industry Q	18,830	2.193	1.082	1.400	1.950	2.642
Bond Rating	15,733	0.437	0.496	0	0	1
WW Index	18,807	-0.300	0.126	-0.394	-0.292	-0.205
Combined Reporting	13,480	0.416	0.309	0.136	0.390	0.667
Combined Reporting (HQ)	18,545	0.406	0.491	0	0	1
Industry Shock Index	18,827	-0.298	1.243	-0.470	-0.166	0.172

Panel B: Correlation Matrix of Key Variables											
Number of Observations: 18,830											
	Bonacich	CAPEX	R&D	Assets	Age	Q	CF	Leverage	Cash	Informa.	Diversifi.
Log(Centrality)	1										
CAPEX	0.024	1									
R&D	0.043	-0.054	1								
Log(Assets)	0.318	0.029	-0.440	1							
Log(Age)	0.095	-0.075	-0.318	0.580	1						
Q	0.086	0.147	0.450	-0.222	-0.238	1					
CF	0.106	0.100	0.027	0.220	0.163	0.054	1				
Leverage	-0.067	0.091	-0.275	0.281	0.176	-0.187	-0.166	1			
Cash Holding	-0.010	-0.122	0.607	-0.435	-0.412	0.411	-0.068	-0.403	1		
Informativeness	-0.180	-0.011	0.241	-0.706	-0.432	0.029	-0.179	-0.086	0.195	1	
Diversification	0.094	-0.065	-0.248	0.340	0.376	-0.174	0.005	0.130	-0.299	-0.227	1

Table 5

Main Results: Alliance Network Centrality and Investment-to-Price Sensitivity

This table shows the impact of alliance network centrality on investment-to-price sensitivity. The dependent variable is capital expenditure (*CAPEX*) in Column (1), capital plus research and development expenditures (*CAPEX + R&D*) in Column (2), *CAPEX + R&D* of firms with non-missing *R&D* in Column (3), and non-missing *R&D* in Column (4). All dependent variables are measured in percentage points. *Log(Centrality)* is the natural logarithm of the Bonacich centrality described in Section 3.2. The main independent variable is the interaction term between *Log(Centrality)* and Tobin's Q, a proxy for price-based investment opportunities. See Appendix 1 for the complete list of variable definitions. See Table 4 for the list of winsorized variables. 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	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Centrality)	0.126	0.879***	1.153***	1.093***
	(1.11)	(4.45)	(4.94)	(5.58)
Log(Centrality) × Q	**-0.117*****	**-0.218*****	**-0.319*****	**-0.206*****
	(-2.97)	**(-3.37)**	**(-4.54)**	**(-3.43)**
Log(Centrality) × CF	0.391	0.738	1.042	0.303
	(1.05)	(1.17)	(1.45)	(0.51)
Q	1.048***	2.083***	2.234***	1.340***
	(12.85)	(15.31)	(14.71)	(10.47)
CF	2.320***	3.779***	3.883***	1.785
	(3.88)	(3.36)	(2.89)	(1.56)
Log(Assets)	-1.075***	-5.550***	-6.712***	-5.879***
	(-7.57)	(-20.18)	(-20.24)	(-20.12)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	18,830	18,830	13,647	13,647
Within R^2	0.193	0.288	0.329	0.263

Table 6

Alternative Explanations: Private Information in Stock Prices / Diversification

This table examines whether the impact of alliance network centrality on investment-to-price sensitivity is driven by two alternative channels that might be captured by alliance network centrality: the volume of private information contained in stock prices and the extent of corporate diversification. The dependent variable is capital expenditure (*CAPEX*) in Column (1) and (2), capital plus research and development expenditures (*CAPEX + R&D*) in Column (3) and (4), *CAPEX + R&D* of firms with non-missing *R&D* in Column (5) and (6), and non-missing *R&D* in Column (7) and (8). All dependent variables are measured in percentage points. *Log(Centrality)* is the natural logarithm of the Bonacich centrality described in Section 3.2. The main independent variable is the interaction term between *Log(Centrality)* and Tobin's Q, a proxy for price-based investment opportunities. See Appendix 1 for the complete list of variable definitions. See Table 4 for the list of winsorized variables. 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	CAPEX		CAPEX + R&D		CAPEX + R&D (non-missing)		R&D (non-missing)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Centrality)	0.122	0.095	0.666***	0.627***	0.915***	0.867***	0.826***	0.823***
	(1.06)	(0.81)	(3.34)	(3.06)	(3.85)	(3.57)	(4.22)	(3.98)
Log(Centrality) × Q	**-0.121*** **	**-0.109*** **	**-0.137** **	**-0.129* **	**-0.232*** **	**-0.220*** **	**-0.104**	**-0.110**
	(-2.94)	**(-2.65)**	**(-2.00)**	**(-1.87)**	**(-3.08)**	**(-2.91)**	**(-1.64)**	**(-1.63)**
Log(Centrality) × CF	0.357	0.390	0.755	0.747	1.094	1.075	0.391	0.345
	(0.96)	(1.06)	(1.20)	(1.17)	(1.55)	(1.46)	(0.67)	(0.55)
Q	1.028***	0.991***	1.658***	1.587***	1.799***	1.778***	0.833***	0.839***
	(10.69)	(7.85)	(9.64)	(7.05)	(9.14)	(7.11)	(4.81)	(3.85)
CF	2.302***	2.341***	3.880***	3.944***	3.950***	3.858***	1.874*	1.815
	(3.87)	(3.69)	(3.49)	(3.35)	(2.99)	(2.70)	(1.67)	(1.47)
Log(Assets)	-1.266***	-1.364***	-5.731***	-6.163***	-6.876***	-7.308***	-5.876***	-6.254***
	(-8.67)	(-8.32)	(-20.70)	(-20.64)	(-20.45)	(-19.57)	(-20.22)	(-19.58)
Informativeness	-0.248***		-0.670***		-0.696***		-0.568***	
	(-3.59)		(-5.95)		(-4.86)		(-4.64)	
Informativeness × Q	-0.005		0.172***		0.174***		0.209***	
	(-0.20)		(3.99)		(3.42)		(4.66)	
PIN		-4.778***		-12.886***		-12.311***		-10.359***
		(-3.17)		(-5.26)		(-4.10)		(-4.06)
PIN × Q		0.185		2.951***		2.608**		3.063***
		(0.29)		(2.59)		(2.01)		(2.82)
Diversification	0.482	0.710	4.255***	4.756***	5.113***	5.259***	4.162***	4.355***
	(0.61)	(0.87)	(3.57)	(3.85)	(3.43)	(3.42)	(4.17)	(4.06)
Diversification × Q	-0.030	-0.083	-1.571**	-1.716**	-1.790**	-1.866**	-1.595***	-1.672***
	(-0.07)	(-0.19)	(-2.31)	(-2.46)	(-2.15)	(-2.19)	(-3.27)	(-3.24)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,830	17,325	18,830	17,325	13,647	12,611	13,647	12,611
Within R^2	0.195	0.194	0.293	0.296	0.334	0.337	0.271	0.273

Table 7

Price Efficiency: The Impact of Regulation SHO Pilot Program

This table examines whether the impact of alliance network centrality on investment-to-price sensitivity is adversely affected by an exogenous increase in stock price efficiency. I exploit the SEC's Regulation SHO that includes a pilot program that reduces the cost of short selling for a randomly chosen group of stocks. See Section 4.2 for more detail on the experiment. The dependent variable is capital expenditure (*CAPEX*) in Column (1) and (2), capital plus research and development expenditures (*CAPEX + R&D*) in Column (3) and (4), *CAPEX + R&D* of firms with non-missing *R&D* in Column (5) and (6), and non-missing *R&D* in Column (7) and (8). All dependent variables are measured in percentage points. *Central* and *Non-central* sub-samples are constructed using the median value of Bonacich centrality around the experiment period. The main independent variable is the triple-interaction term between Tobin's Q, a proxy for price-based investment opportunities, *Pilot* which indicates the experiment stocks, and *During* which indicates the experiment period. See Appendix 1 for the complete list of variable definitions. See Table 4 for the list of winsorized variables. 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	CAPEX		CAPEX + R&D		CAPEX + R&D (non-missing)		R&D (non-missing)	
Sub-sample	Central	Non-Central	Central	Non-Central	Central	Non-Central	Central	Non-Central
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Q	0.523***	0.388**	1.125**	1.374***	1.007	1.428***	0.491	0.995**
	(3.44)	(2.44)	(2.00)	(3.53)	(1.60)	(3.30)	(0.86)	(2.32)
Q × Pilot	0.024	0.700**	-0.428	0.362	-0.514	0.311	-0.531	-0.438
	(0.11)	(2.09)	(-0.68)	(0.55)	(-0.74)	(0.41)	(-0.85)	(-0.69)
Q × During	-0.121	0.628***	0.643	0.670	0.999*	0.746	1.032**	0.097
	(-0.69)	(3.04)	(1.31)	(1.58)	(1.81)	(1.49)	(2.31)	(0.25)
Q × Pilot × During	**0.476***	**-0.947*****	**1.854****	**-0.867**	**2.023****	**-1.055**	**1.646****	**0.405**
	(1.72)	**(-2.61)**	**(2.33)**	**(-1.28)**	**(2.24)**	**(-1.20)**	**(1.99)**	**(0.57)**
During	-0.484	-2.090*	-1.773	-0.834	-2.848*	-0.526	-1.955	2.153
	(-0.79)	(-1.82)	(-1.31)	(-0.52)	(-1.74)	(-0.24)	(-1.43)	(1.50)
Pilot × During	-0.792	0.997	-3.241**	0.633	-3.675**	1.080	-3.028*	-1.264
	(-1.21)	(1.16)	(-2.09)	(0.44)	(-1.99)	(0.57)	(-1.81)	(-0.82)
Q	0.581***	1.650***	0.581***	1.650***	1.811***	1.234***	1.234***	1.234***
	(6.25)	(5.29)	(6.25)	(5.29)	(5.40)	(3.87)	(3.87)	(3.87)
CF	2.487***	2.876***	1.869	3.579	1.611	4.285	-0.777	1.347
	(4.45)	(2.99)	(1.52)	(1.59)	(1.13)	(1.56)	(-0.64)	(0.60)
Log(Assets)	-0.764***	-0.743**	-4.914***	-5.014***	-6.304***	-5.835***	-5.597***	-5.714***
	(-3.61)	(-2.21)	(-6.74)	(-5.85)	(-7.25)	(-5.21)	(-6.86)	(-5.59)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,677	1,675	1,677	1,675	1,286	1,260	1,286	1,260
R^2	0.120	0.116	0.186	0.184	0.210	0.200	0.186	0.167

Table 8

The Impact of Financial Constraints: Sub-sample Tests

This table examines whether the impact of alliance network centrality on investment-to-price sensitivity is stronger for financially unconstrained firms than for financially constrained firms. The dependent variable is capital expenditure (*CAPEX*) in Columns (1) and (2), capital plus research and development expenditures (*CAPEX + R&D*) in Columns (3) and (4), *CAPEX + R&D* of firms with non-missing *R&D* in Columns (5) and (6), and non-missing *R&D* in Columns (7) and (8). To construct a sub-sample of financially unconstrained and constrained firms, I use the following measures of financial constraints: total assets (*Firm Size*), the availability of corporate bond rating (*Bond Rating*), and the Whited and Wu Index (*WW Index*). Sub-samples are double-sorted (first by the Bonacich centrality and second by the measure of financial constraints) to balance the dispersion of alliance network centrality within each sub-sample. All dependent variables are measured in percentage points. *Log(Centrality)* is the natural logarithm of the Bonacich centrality described in Section 3.2. The main independent variable is the interaction term between *Log(Centrality)* and Tobin's Q, a proxy for price-based investment opportunities. Only the coefficients of interest are reported for a brevity (full coefficients in Internet Appendix Table 2). See Appendix 1 for the complete list of variable definitions. See Table 4 for the list of winsorized variables. 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	CAPEX		CAPEX + R&D		CAPEX + R&D (non-missing)		R&D (non-missing)	
FC Measure: Firm Size	Large (1)	Small (2)	Large (3)	Small (4)	Large (5)	Small (6)	Large (7)	Small (8)
Log(Centrality) × Q	**-0.258*****	**-0.013**	**-0.307*****	**0.036**	**-0.354*****	**-0.030**	**-0.116**	**0.015**
	(-3.29)	**(-0.24)**	**(-2.79)**	**(0.35)**	**(-3.12)**	**(-0.26)**	**(-1.51)**	**(0.17)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,414	9,416	9,414	9,416	5,972	7,675	5,972	7,675
Within R^2	0.218	0.162	0.260	0.269	0.321	0.301	0.169	0.266
FC Measure: Bond Rating	Yes (1)	No (2)	Yes (3)	No (4)	Yes (5)	No (6)	Yes (7)	No (8)
Log(Centrality) × Q	**-0.279*****	**-0.040**	**-0.377*****	**0.038**	**-0.383*****	**-0.018**	**-0.154**	**0.003**
	(-2.71)	**(-0.62)**	**(-2.81)**	**(0.34)**	**(-2.80)**	**(-0.14)**	**(-1.51)**	**(0.03)**
Controls and FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,874	8,859	6,874	8,859	4,179	6,729	4,179	6,729
Within R^2	0.226	0.172	0.241	0.316	0.294	0.361	0.122	0.326
FC Measure: WW Index	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)	Low (7)	High (8)
Log(Centrality) × Q	**-0.278*****	**-0.011**	**-0.371*****	**-0.010**	**-0.438*****	**-0.080**	**-0.170****	**-0.021**
	(-4.53)	**(-0.20)**	**(-4.09)**	**(-0.11)**	**(-4.51)**	**(-0.73)**	**(-2.17)**	**(-0.22)**
Controls and FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,414	9,416	9,414	9,416	5,972	7,675	5,972	7,675
Within R^2	0.218	0.162	0.260	0.269	0.321	0.301	0.169	0.266

Table 9

The Impact of Financial Constraints: The 2007-2008 Financial Crisis

This table uses the 2007-2008 financial crisis to test whether an exogenous shock in firms' financial constraints dampens the negative relation between alliance network centrality and investment-to-price sensitivity. The dependent variable is capital expenditure (*CAPEX*) in Column (1), capital plus research and development expenditures (*CAPEX + R&D*) in Column (2), *CAPEX + R&D* of firms with non-missing *R&D* in Column (3), and non-missing *R&D* in Column (4). All dependent variables are measured in percentage points. *Log(Centrality)* is the natural logarithm of the Bonacich centrality described in Section 3.2. The main independent variable is the triple-interaction term between *Log(Centrality)*, Tobin's Q, a proxy for price-based investment opportunities, and *DD1Due* which measures the unexpected financial pressure due to the financial crisis. See Appendix 1 for the complete list of variable definitions. See Table 4 for the list of winsorized variables. 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	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Centrality)	-2.309***	2.919*	4.450**	6.046***
	(-2.98)	(1.84)	(2.51)	(3.25)
Log(Centrality) × Q	0.118	-1.405*	-1.929**	-1.814**
	(0.34)	(-1.76)	(-2.29)	(-2.04)
Log(Centrality) × Q × DD1Due	**0.317**	**6.005****	**6.759****	**6.285****
	(0.41)	**(2.24)**	**(2.35)**	**(2.03)**
Log(Centrality) × DD1Due	1.069	-11.542*	-14.927**	-14.895**
	(0.57)	(-1.80)	(-2.14)	(-2.01)
Q × DD1Due	0.750	0.047	-0.682	-1.183
	(1.01)	(0.02)	(-0.21)	(-0.36)
DD1Due	-4.410***	1.283	4.079	6.330
	(-2.62)	(0.19)	(0.55)	(0.84)
Q	0.195	4.000***	4.381***	3.813***
	(0.48)	(4.75)	(4.89)	(3.92)
Log(Centrality) × CF	0.181	9.710	13.279*	9.546
	(0.09)	(1.53)	(1.71)	(1.30)
CF	3.516	4.183	0.753	0.487
	(1.61)	(0.63)	(0.10)	(0.07)
Log(Assets)	0.654***	-1.901***	-2.573***	-3.093***
	(3.87)	(-4.90)	(-5.69)	(-6.84)
Observations	512	512	365	365
Adjusted R^2	0.066	0.289	0.366	0.377

Table 10

Endogeneity: Controlling for the Influence of Alliance Initiation

This table addresses the endogeneity issues in alliance network centrality by controlling for the firm-year observations with new alliances in two different approaches. The first method is to control for firm-cohort fixed effects (Firm-Cohort FE) that assigns a firm-cohort dummy for each firm-year observation with new alliances, thereby relying on the within-firm variation of alliance network centrality without new alliances. The second method is to examine the impact of indirectly connected parts of alliance network centrality using a sample of firm-year observations experiencing no changes in their direct alliance connections. The dependent variable is capital expenditure (*CAPEX*) in Columns (1) and (5), capital plus research and development expenditures (*CAPEX + R&D*) in Columns (2) and (6), *CAPEX + R&D* of firms with non-missing *R&D* in Columns (3) and (7), and non-missing *R&D* in Columns (4) and (8). All dependent variables are measured in percentage points. *Log(Centrality)* is the natural logarithm of the Bonacich centrality described in Section 3.2. *Log(Degree)* is the natural logarithm of the degree centrality that equals the number of direct connections. *Log(Indirect + 1)* is one plus the natural logarithm of the indirect centrality that equals the difference between Bonacich and degree centrality. The main independent variable is the interaction term between *Log(Centrality)* (Columns 1 – 4) or *Log(Indirect + 1)* (Columns 5 – 8) and Tobin's Q, a proxy for price-based investment opportunities. See Appendix 1 for the complete list of variable definitions. See Table 4 for the list of winsorized variables. 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	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Centrality)	-0.057	0.249	0.586*	0.549*				
	(-0.35)	(0.85)	(1.65)	(1.91)				
Log(Centrality) × Q	**-0.048**	**-0.134**	**-0.213***	**-0.157***				
	(-0.83)	**(-1.29)**	**(-1.84)**	**(-1.65)**				
Log(Indirect + 1)					0.628**	1.154**	1.003	0.775
					(2.06)	(2.17)	(1.55)	(1.59)
Log(Indirect + 1) × Q					**-0.254****	**-0.324***	**-0.244**	**-0.147**
					(-2.36)	**(-1.69)**	**(-1.18)**	**(-0.90)**
Log(Degree)					-0.505	-0.261	0.257	0.249
					(-1.19)	(-0.40)	(0.33)	(0.37)
Log(Degree) × Q					0.260	0.306	0.015	0.087
					(1.30)	(1.02)	(0.05)	(0.30)

Continued…

Table 10 (Continued)

Q	0.984***	1.597***	1.673***	0.841***	1.032***	1.687***	1.726***	0.879***
	(8.88)	(8.25)	(7.33)	(4.16)	(7.60)	(6.81)	(5.88)	(3.22)
CF	2.786***	3.930***	3.709***	0.918	2.207***	2.294**	3.201**	0.556
	(7.92)	(5.24)	(4.17)	(1.20)	(4.19)	(2.16)	(2.52)	(0.53)
Log(Assets)	-2.355***	-8.374***	-10.249***	-8.222***	-1.193***	-5.284***	-6.973***	-5.779***
	(-10.91)	(-19.90)	(-19.50)	(-17.92)	(-5.16)	(-12.24)	(-12.90)	(-13.52)
Informativeness	-0.083	-0.333***	-0.472***	-0.371***	-0.111	-0.412***	-0.461**	-0.344*
	(-1.08)	(-2.81)	(-3.10)	(-2.97)	(-1.22)	(-2.69)	(-2.24)	(-1.96)
Informativeness × Q	-0.047	0.072	0.077	0.129***	-0.038	0.099	0.074	0.118
	(-1.54)	(1.50)	(1.37)	(2.65)	(-0.94)	(1.45)	(0.90)	(1.57)
Diversification	1.413*	4.314***	4.839***	3.595***	-0.067	2.067	2.343	2.604*
	(1.80)	(3.26)	(2.90)	(3.05)	(-0.05)	(1.03)	(0.84)	(1.93)
Diversification × Q	-0.213	-1.319*	-1.035	-1.014*	0.325	-0.617	-0.439	-1.197*
	(-0.56)	(-1.89)	(-1.20)	(-1.77)	(0.41)	(-0.52)	(-0.26)	(-1.69)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	No	No	No	No
Observations	18,830	18,830	13,647	13,647	8,346	8,346	5,827	5,827
Within R^2	0.136	0.233	0.279	0.245	0.145	0.227	0.272	0.225

Table 11

Self-selection: Heckman Model Using Combined Reporting Index

This table examines self-selection issues regarding the choice of participating in alliance networks using Heckman two-step procedure of sample selection model. The first stage estimates a Probit regression model in which the dependent variable is an indicator variable that equals 1 if a firm is inside alliance network, 0 otherwise (Columns 1 and 4). The instrument is *Combined Reporting* that is a firm-level index of combined income reporting requirement based on the geographic dispersion of firm operations (Section 3.3). The second stage estimates an OLS regression model in which the dependent variable is capital expenditure (*CAPEX*) in Column (2), capital plus research and development expenditures (*CAPEX + R&D*) in Column (3), *CAPEX + R&D* of firms with non-missing *R&D* in Column (5), and non-missing *R&D* in Column (6). All dependent variables are measured in percentage points. *Log(Centrality)* is the natural logarithm of the Bonacich centrality described in Section 3.2. See Appendix 1 for the complete list of variable definitions. See Table 4 for the list of winsorized variables. 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.

Estimation	1st Stage	2nd Stage		1st Stage	2nd Stage	
Dependent Variable	Inside Network?	CAPEX	CAPEX + R&D	Inside Network?	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Centrality)		0.088	1.998***		2.561***	2.323***
		(1.07)	(12.16)		(12.68)	(12.98)
Log(Centrality) × Q		**-0.133*****	**-0.300*****		**-0.391*****	**-0.231*****
		(-5.76)	**(-6.31)**		**(-7.29)**	**(-4.85)**
Log(Centrality) × CF		0.264	2.736***		3.193***	2.249***
		(1.08)	(5.71)		(5.77)	(4.59)
Q	0.010	0.968***	2.119***	0.012	2.316***	1.365***
	(1.30)	(16.10)	(16.53)	(1.50)	(15.61)	(10.35)
CF	-0.432***	2.793***	8.720***	-0.332***	6.752***	5.177***
	(-9.51)	(6.16)	(9.31)	(-6.79)	(6.36)	(5.49)
Log(Assets)	0.292***	-0.044	-4.680***	0.277***	-4.985***	-4.834***
	(45.34)	(-0.40)	(-19.44)	(37.91)	(-19.22)	(-20.96)
Informativeness	-0.089***	-0.106	-0.464***	-0.104***	-0.452**	-0.417**
	(-12.06)	(-1.59)	(-3.22)	(-12.09)	(-2.41)	(-2.49)
Informativeness × Q	0.014***	-0.007	0.185***	0.017***	0.149***	0.169***
	(6.09)	(-0.42)	(5.04)	(6.54)	(3.43)	(4.34)
Diversification	-0.043	-2.218***	0.459	-0.077	0.653	2.421**
	(-0.59)	(-4.88)	(0.45)	(-0.95)	(0.52)	(2.16)
Diversification × Q	0.156***	0.581***	-2.473***	0.183***	-2.586***	-2.927***
	(4.68)	(3.09)	(-5.68)	(5.06)	(-5.13)	(-6.51)
Combined Reporting	**0.183*****			**0.253*****		
	(7.35)			**(9.22)**		
Inverse Mills Ratio		-0.220	-12.604***		-12.268***	-11.158***
		(-0.37)	(-9.86)		(-8.55)	(-8.75)
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38,255	13,252	13,252	34,849	9,846	9,846

Table 12

The Impact of Alliance Types: R&D vs. Non-R&D Alliances

This table examines the impact of alliance types by calculating Bonacich centrality in two sub-networks based on alliance types: R&D and Non-R&D alliances. Specifically, R&D alliances include licensing agreements, R&D agreements, and technology transfer agreements. Non-R&D alliances include joint ventures, manufacturing agreements, and marketing agreements, excluding any overlapping deal with R&D alliances. Sample firms are divided into two groups based on the ratio of the number of participating R&D alliances to total number of participating alliances: above median (*High*) and below median (*Low*). The dependent variable is capital expenditure (*CAPEX*) in Columns (1) and (2), and non-missing research and development expenditure (*R&D*) in Columns (3) and (4). All dependent variables are measured in percentage points. *Log(Centrality)* is the natural logarithm of the Bonacich centrality described in Section 3.2. See Appendix 1 for the complete list of variable definitions. See Appendix 1 for the complete list of variable definitions. See Table 4 for the list of winsorized variables. 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	CAPEX		R&D (non-missing)	
Ratio of R&D Alliances to Total Alliances	High	Low	High	Low
	(1)	(2)	(3)	(4)
Log(Centrality)	-0.072	0.025	0.867**	0.506**
	(-0.41)	(0.12)	(2.55)	(2.09)
Log(Centrality) × Q	**-0.058**	**-0.151***	**-0.170****	**-0.098**
	(-1.32)	**(-1.92)**	**(-2.22)**	**(-0.93)**
Log(Centrality) × CF	0.453	0.486	0.318	0.402
	(0.97)	(0.92)	(0.37)	(0.42)
Q	0.752***	1.166***	1.163***	0.706***
	(6.14)	(6.57)	(4.69)	(2.61)
CF	2.283***	1.843*	2.150	1.144
	(2.66)	(1.75)	(1.18)	(0.58)
Log(Assets)	-0.994***	-1.894***	-8.036***	-4.086***
	(-5.26)	(-7.42)	(-17.93)	(-10.03)
Informativeness	-0.305***	-0.286***	-0.631***	-0.323*
	(-3.22)	(-2.71)	(-3.39)	(-1.90)
Informativeness × Q	0.047	-0.015	0.163***	0.145**
	(1.44)	(-0.43)	(2.83)	(2.05)
Diversification	1.452	0.992	3.150**	3.179**
	(1.55)	(0.96)	(2.26)	(2.14)
Diversification × Q	-0.517	-0.389	-1.980***	-1.080
	(-1.25)	(-0.64)	(-4.25)	(-1.30)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	8,127	8,111	6,753	5,419
Within R^2	0.176	0.195	0.311	0.210

Table 13

Robustness Tests

This table tests the robustness of the negative impact of alliance network centrality on investment-to-price sensitivity. The dependent variable is capital expenditure (*CAPEX*) in Column (1), capital plus research and development expenditures (*CAPEX* + *R&D*) in Column (2), *CAPEX* + *R&D* of firms with non-missing *R&D* in Column (3), and non-missing *R&D* in Column (4). All dependent variables are measured in percentage points. Specifications (1) – (7) use alternative settings of investment regressions. Specification (1) estimates the cumulant estimator of Erickson, Jiang and Whited (2014) that provides unbiased estimates of coefficients in errors-in-variables panel regressions. Specification (2) uses Total Q (Peters and Taylor 2017) that incorporates both tangible and intangible capital in estimating firms' total capital to measure price-based investment opportunities. Specification (3) uses a value-weighted industry-level (SIC 3-digit) Tobin's Q to measure price-based investment opportunities. Specification (4) includes the square-term of Tobin's Q to control for the potential non-linearity in investment-to-price sensitivity. Specification (5) controls for additional set of firm characteristics that may affect investment decisions: firm age, sales growth, book leverage, and cash holding. Specification (6) excludes firms experiencing more than 20% of changes in total assets to isolate the impact of firms with ongoing material changes in operations. Specification (7) reports the cross-sectional differences in the impact of alliance network centrality on investment-to-price sensitivity by estimating Fama-MacBeth regressions (Fama and MacBeth 1973). Specifically, the reported coefficients are the average of cross-sectional coefficients estimated each alliance network between 1994 and 2013 with industry (SIC 3-digit) fixed effects. Specifications (8) – (11) test alternative assumptions for the construction of alliance networks. Specifications (8) and (9) test the robustness of results for alternative assumptions on alliance duration: 3- and 7-year (see Section 2.1). Specification (10) uses centrality measures constructed from alliance networks consisting of alliance deals involving at least two U.S. firms in Compustat/CRSP merged database. Specification (11) uses centrality measures constructed from alliance networks consisting of entire global alliance deals involving not only firms but also universities, government agencies, and other institutions. Specifications (12) – (16) test the robustness of results for alternative measures of network centrality. Specification (12) uses the degree centrality that only counts for the impact of direct connections. Specifications (13) and (14) use alternative parameter choices for the calculation of Bonacich centrality. Specifications (15) and (16) check the robustness of results using eigenvector and betweenness centrality. See Section 3.2 and Appendix 2 for more detail on various measures of network centrality. Only the coefficients of interest are reported for a brevity. The reported coefficient is associated with the interaction term between *Log(Centrality)* and Tobin's Q, a proxy for price-based investment opportunities. All specifications include the same set of control variables in Column (1) of Table 6 with calendar year and firm fixed effects (except for Specification 1 that uses the baseline model in Table 5). See Appendix 1 for the complete list of variable definitions. See Table 4 for the list of winsorized variables. 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		CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
		(1)	(2)	(3)	(4)
Alternative Setting of Investment Regression					
Cumulant Estimator (Erickson, Jiang and Whited 2014)	(1)	-1.982***	-2.105***	-2.404***	-3.061***
		(-6.95)	(-6.52)	(-6.29)	(-4.50)

Continued…

Table 13 (Continued)

Total Q (Peters and Taylor 2017)	(2)	-0.094***	-0.113***	-0.171***	-0.066*
		(-3.20)	(-2.58)	(-3.52)	(-1.74)
Industry Q	(3)	-0.154***	-0.212**	-0.310***	-0.155*
		(-3.11)	(-2.47)	(-2.98)	(-1.88)
Non-linearity: Controlling for Q^2	(4)	-0.103**	-0.124*	-0.225***	-0.108*
		(-2.47)	(-1.79)	(-2.96)	(-1.71)
More Controls: Age, Sales Growth, Leverage, and Cash	(5)	-0.129***	-0.148**	-0.239***	-0.106*
		(-3.19)	(-2.22)	(-3.24)	(-1.70)
Excluding Firms with More than 20% of Asset Changes	(6)	-0.067*	-0.075	-0.190**	-0.115*
		(-1.89)	(-1.01)	(-2.24)	(-1.68)
Fama-MacBeth Regressions	(7)	-0.066	-0.104	-0.300*	-0.275**
		(-1.54)	(-1.06)	(-1.96)	(-2.12)
Alternative Assumption for Alliance Network Construction					
3-year Alliance Duration	(8)	-0.126***	-0.146*	-0.245***	-0.110
		(-2.59)	(-1.89)	(-2.92)	(-1.56)
7-year Alliance Duration	(9)	-0.114***	-0.120*	-0.196***	-0.078
		(-3.11)	(-1.93)	(-2.83)	(-1.33)
Within U.S. Networks	(10)	-0.107**	-0.128*	-0.214***	-0.113
		(-2.40)	(-1.71)	(-2.61)	(-1.59)
Entire Global Networks	(11)	-0.076***	-0.102**	-0.157***	-0.072*
		(-3.19)	(-2.57)	(-3.55)	(-1.91)
Alternative Measures of Network Centrality					
Bonacich-	(12)	-0.134***	-0.138*	-0.241***	-0.095
		(-2.75)	(-1.75)	(-2.77)	(-1.29)
Bonacich+	(13)	-0.088***	-0.109**	-0.180***	-0.093**
		(-2.98)	(-2.17)	(-3.23)	(-2.00)
Degree	(14)	-0.129**	-0.116	-0.216**	-0.072
		(-2.44)	(-1.38)	(-2.31)	(-0.90)
Eigenvector	(15)	-0.075**	-0.124**	-0.184***	-0.123***
		(-2.51)	(-2.46)	(-3.37)	(-2.67)
Betweenness	(16)	-3.748	-13.634*	-18.797***	-13.796***
		(-0.45)	(-1.95)	(-3.59)	(-2.88)

Table 14

Alliance Network Centrality and Market Valuation

This table examines the impact of alliance network centrality on market valuation. The dependent variable is Tobin's Q. The main independent variable is the interaction term between *Log(Centrality)*, the natural logarithm of the Bonacich centrality described in Section 3.2. All independent variables are lagged by one year. Column (1) reports the estimation results for the full sample. Columns (2) – (7) report the estimation results for a sub-sample of financially unconstrained and constrained firms, using the same three measures of financial constraints in Table 8: *Firm Size* (Columns 2 and 3), *Bond Rating*, and *WW Index* (Columns 6 and 7). Sub-samples are double-sorted (first by the Bonacich centrality and second by the measure of financial constraints) to balance the dispersion of alliance network centrality within each sub-sample. See Appendix 1 for the complete list of variable definitions. See Table 4 for the list of winsorized variables. 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: Tobin's Q	Full Sample	Sub-sample: Financial Constraints					
		Firm Size		Bond Rating		WW Index	
		Large	Small	Yes	No	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(Centrality)	**0.029**	**0.064****	**-0.039**	**0.064*****	**-0.013**	**0.055****	**-0.007**
	(1.20)	**(2.39)**	**(-0.88)**	**(2.79)**	**(-0.29)**	**(2.02)**	**(-0.15)**
Log(Assets)	-0.666***	-0.576***	-0.780***	-0.505***	-0.610***	-0.587***	-0.813***
	(-16.86)	(-8.90)	(-14.05)	(-8.61)	(-11.80)	(-10.09)	(-14.47)
Log(Age)	-0.492***	-0.292**	-0.416**	-0.188	-0.523***	-0.387***	-0.438**
	(-4.64)	(-1.99)	(-2.13)	(-1.14)	(-2.97)	(-2.58)	(-2.21)
ROA	0.817***	2.950***	0.133	2.705***	0.182	3.033***	0.163
	(5.04)	(7.44)	(0.83)	(5.96)	(0.88)	(8.07)	(0.96)
PPE	-0.678***	-0.572**	-1.222***	-0.151	-0.917**	-0.530**	-1.219***
	(-2.97)	(-2.30)	(-3.18)	(-0.61)	(-2.41)	(-2.14)	(-3.21)
R&D	1.918***	3.637***	0.973**	2.951**	1.757***	4.554***	0.999**
	(5.35)	(3.46)	(2.51)	(2.11)	(3.80)	(4.41)	(2.45)
CAPEX	0.413	-0.191	0.608	-0.223	0.166	-0.007	0.818*
	(1.28)	(-0.50)	(1.21)	(-0.55)	(0.37)	(-0.02)	(1.69)
Leverage	-1.862	3.990***	-3.695**	6.652***	-2.723*	3.732**	-3.640**
	(-1.51)	(2.58)	(-2.27)	(3.83)	(-1.68)	(2.23)	(-2.35)
Return Volatility	-1.788	3.894**	-3.632**	6.524***	-2.701*	3.584**	-3.545**
	(-1.46)	(2.54)	(-2.23)	(3.82)	(-1.67)	(2.15)	(-2.29)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,830	9,414	9,416	6,874	8,859	9,404	9,426
Within R^2	0.190	0.255	0.167	0.240	0.162	0.267	0.182

Table 15

Alliance Network Centrality and Value Response to Industry-Specific Shock

This table examines the impact of alliance network centrality on the value responses to industry-level shocks. The dependent variable is the change in Tobin's Q between year *t* – *1* and *t* (*ΔQ*). *Log(Centrality)* is the natural logarithm of the Bonacich centrality described in Section 3.2. The main independent variable is the interaction term between *Log(Centrality)* and *Industry Shock Index* (*Positive* or *Negative Industry Shock*), which is the principal component of seven variables that proxy for industry status (Harford 2005). *Positive (Negative) Industry Shock* is an indicator variable if *Industry Shock Index* belongs to the top (bottom) 10th percentile of the index distributions. All *Industry Shock* variables are measured at year *t* to test whether the informational advantages from alliance networks help more central firms to better anticipate future industry conditions. See Appendix 1 for the complete list of variable definitions. 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)
Log(Centrality)	0.012	-0.029	0.006	-0.044
	(0.69)	(-0.75)	(0.33)	(-1.18)
Log(Centrality) × Industry Shock Index	**0.033****	**0.059****		
	(1.99)	**(2.28)**		
Industry Shock Index	0.064***	0.045*		
	(2.99)	(1.76)		
Log(Centrality) × Positive Industry Shock			**0.060***	**0.166****
			(1.65)	**(2.46)**
Positive Industry Shock			0.063	0.001
			(0.98)	(0.01)
Log(Centrality) × Negative Industry Shock			**-0.061**	**-0.140***
			(-1.30)	**(-1.77)**
Negative Industry Shock			-0.320***	-0.238***
			(-4.60)	(-2.80)
Log(Assets)	-0.093***	-0.031	-0.096***	-0.034
	(-3.43)	(-0.52)	(-3.57)	(-0.58)
Log(Age)	0.386***	0.256	0.367***	0.246
	(5.57)	(1.28)	(5.32)	(1.23)
ROA	-1.376***	-1.464***	-1.373***	-1.458***
	(-7.67)	(-6.10)	(-7.67)	(-6.08)
PPE	0.779***	0.199	0.776***	0.172
	(3.94)	(0.56)	(3.93)	(0.49)
R&D	0.053	-0.134	0.044	-0.155
	(0.13)	(-0.24)	(0.11)	(-0.28)
CAPEX	-2.296***	-1.925***	-2.296***	-1.884***
	(-5.97)	(-3.67)	(-5.96)	(-3.62)
Leverage	0.422***	0.690***	0.413***	0.689***
	(3.61)	(3.64)	(3.52)	(3.66)
Return Volatility	-1.592	2.646	-1.810	2.407
	(-1.09)	(1.41)	(-1.24)	(1.29)
Year FE	Yes	Yes	Yes	Yes
Firm or Firm-cohort FE	Firm	Firm-cohort	Firm	Firm-cohort
Within R^2	0.109	0.099	0.110	0.100

Table 16

Summary of Alliance Announcements

This table reports the summary statistics for alliance announcements. The event study sample contains 3,391 alliance announcements between two U.S. public firms in Compustat/CRSP merged database. Sample announcements range from 1995 to 2013 to restrict the sample to firms with a non-missing value of alliance network centrality in the previous year of announcement. All dollar denominated variables are deflated to 2009 dollars using U.S. GDP deflator. Cumulative abnormal returns (*CAR*) are estimated over a 3-day (-1, 1) event-period using market-adjusted returns (CRSP value-weighted index). *Combined CAR* is a value-weighted CAR of the portfolio of two firms, where the weight is determined by each firm's market capital measured 50 trading days before the announcement. *Combined Dollar Gain* is the sum of firms' dollar wealth gain calculated as CAR multiplied by each firm's market capital at the beginning of the 3-day event period. *Combined Centrality* is the sum of two firms' Bonacich centrality measured in the previous year of announcement. *Both Central* is an indicator variable that equals 1 if both firms' centrality values are above the median of centrality distribution within the event study sample, and 0 otherwise. *One Central* is an indicator variable that equals 1 if only one firm's centrality value is above the median of the centrality distribution within the event study sample, and 0 otherwise. *Combined Market Capital* is the sum of two firms' market capital measured 50 trading days before the announcement. All variables are winsorized at the 1st and 99th percentiles, except for *Both Central, R&D Alliance, Non-R&D Alliance,* and *Horizontal Alliance.* See Appendix 1 for the complete list of variable definitions.

	Obs.	Mean	Std.	P25	Median	P75
Wealth Effects						
CAR (%)	6,782	0.959	6.777	-2.234	0.176	3.004
Combined CAR (%)	3,391	0.128	4.002	-1.869	-0.024	2.026
Combined Dollar Gain ($ million)	3,391	8.001	3,680.859	-501.300	-1.490	527.732
Independent Variables						
Both Central	3,391	0.287	0.452	0	0	1
One Central	3,391	0.426	0.495	0	0	1
Combined Centrality	3,391	113.801	123.392	17.929	57.013	181.854
Combined Market Capital ($ billion)	3,391	75.235	103.104	8.280	33.535	98.708
R&D Alliance	3,391	0.431	0.495	0	0	1
Non-R&D Alliance	3,391	0.315	0.465	0	0	1
Horizontal Alliance	3,391	0.278	0.448	0	0	1

Table 17

Increase in Centrality and Announcement Wealth Effects

This table investigates whether the stock market reacts more positively to the announcement of alliances if new alliances more largely increase the announcing firm's alliance network centrality. The dependent variables are the cumulative abnormal returns (*CAR*) estimated over a 3-day (-1, 1) event-period using market-adjusted returns (CRSP value-weighted index). *Log(Centrality) (at t – 1)* is the natural logarithm of the Bonacich centrality described in Section 3.2, measured at the previous year of alliance announcements. The main independent variable is *Log(ΔBonacich)* which measures the increase in Bonacich centrality of the announcing firm, calculated as the natural logarithm of one plus Bonacich centrality of alliance partner firm multiplied by 0.02 (see Section 5.3 for more detail on the calculation). See Appendix 1 for the complete list of variable definitions. See Table 16 for the list of winsorized variables. Industry fixed effects are defined at the SIC 2-digit level. 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.

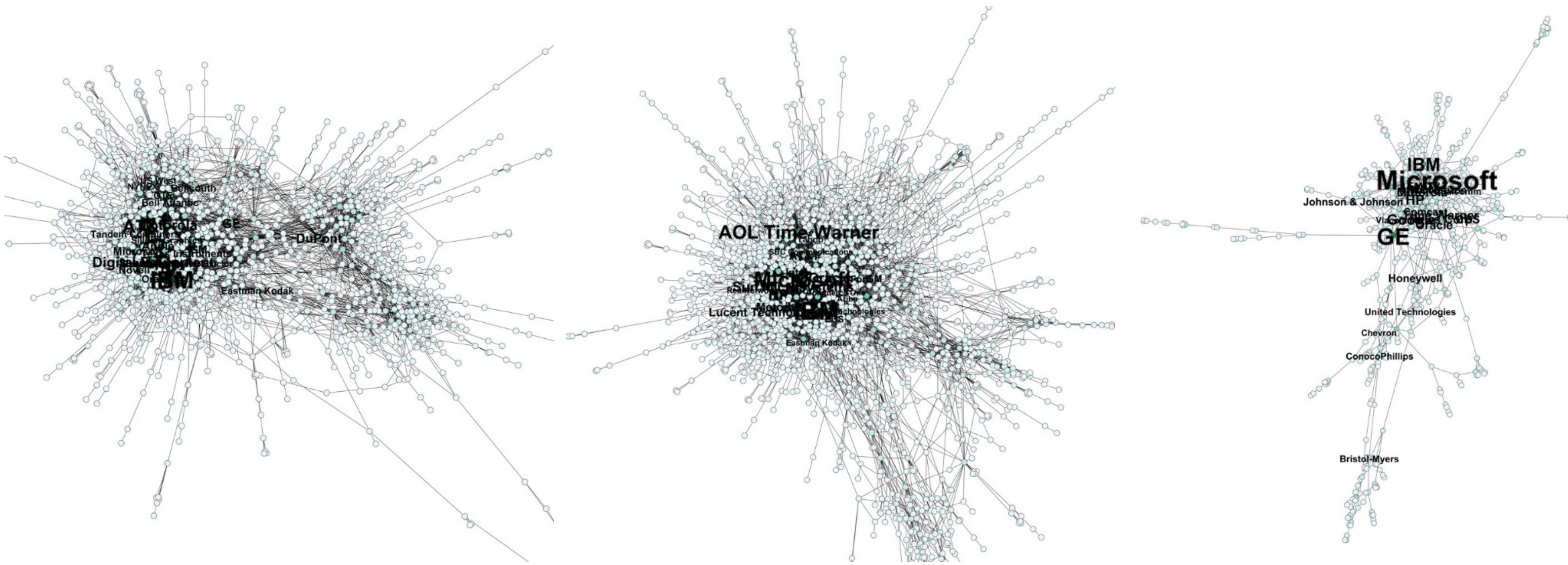
Dependent Variable	3-day Market-Adjusted CAR			
	(1)	(2)	(3)	(4)
Log(Centrality) (at t – 1)	0.209***	0.282***	0.140*	0.207**
	(2.68)	(2.85)	(1.80)	(2.13)
Log(ΔBonacich)	**0.699*** **	**0.801*** **	**0.718*** **	**0.803*** **
	(4.24)	**(4.68)**	**(4.35)**	**(4.69)**
R&D Alliance	0.418*	0.213	0.318	0.173
	(1.77)	(0.86)	(1.35)	(0.70)
Non-R&D Alliance	-0.021	-0.003	0.003	0.001
	(-0.10)	(-0.02)	(0.01)	(0.00)
Horizontal Alliance	0.454**	0.330	0.303	0.295
	(2.21)	(1.48)	(1.51)	(1.34)
Log(Market Capital)	-0.586***	-0.647***	-0.345***	-0.384***
	(-9.31)	(-8.85)	(-5.02)	(-4.74)
ROA			-4.266***	-4.277***
			(-4.83)	(-4.46)
Cash Holding			1.457***	1.391**
			(2.62)	(2.29)
Leverage			0.563	0.539
			(0.93)	(0.78)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	6,782	6,782	6,782	6,782
Adjusted R^2	0.041	0.054	0.053	0.065

Table 18

Synergy: Combined Centrality and Combined Announcement Wealth Effects

This table investigates whether the stock market reacts more positively to the announcement of alliances involving firms more centrally located in alliance networks. Cumulative abnormal returns (*CAR*) are estimated over a 3-day (-1, 1) event-period using market-adjusted returns (CRSP value-weighted index). In Columns (1) and (3), the dependent variable is *Combined CAR* which is a value-weighted *CAR* of the portfolio of two firms, where the weight is determined by each firm's market capital measured 50 trading days before the announcement. In Columns (2) and (4), the dependent variable is *Combined Dollar Gain* that is the sum of firms' dollar wealth gain calculated as CAR multiplied by each firm's market capital at the beginning of the 3-day event period. *Combined CAR* is measured in percentage points, and *Combined Dollar Gain* is measured in million dollars. *Both Central* is an indicator variable that equals 1 if both firms' centrality values are above the median of centrality distribution within the event study sample, and 0 otherwise. *One Central* is an indicator variable that equals 1 if only one firm's centrality value is above the median of the centrality distribution within the event study sample, and 0 otherwise. *Combined Centrality* is the sum of two firms' Bonacich centrality measured in the previous year of announcement. See Appendix 1 for the complete list of variable definitions. See Table 14 for the list of winsorized variables. 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	Combined CAR (1)	Combined Dollar Gain (2)	Combined CAR (3)	Combined Dollar Gain (4)
Both Central	**0.613*****	**564.943*****		
	(2.69)	**(3.07)**		
One Central	0.057	65.722		
	(0.28)	(0.52)		
Combined Centrality			**0.001****	**0.380**
			(2.03)	**(0.45)**
R&D Alliance	0.091	-89.287	0.067	-104.927
	(0.46)	(-0.48)	(0.34)	(-0.56)
Non-R&D Alliance	0.145	192.698	0.129	175.741
	(0.73)	(0.97)	(0.65)	(0.88)
Horizontal Alliance	0.127	104.284	0.127	99.763
	(0.76)	(0.75)	(0.76)	(0.71)
Combined Market Capital ($ billion)	-0.002**	-2.256	-0.002**	-1.729
	(-2.09)	(-1.38)	(-2.07)	(-1.01)
Year FE	Yes	Yes	Yes	Yes
Observations	3,391	3,391	3,391	3,391
R^2	0.008	0.013	0.006	0.010



(A) Alliance Network in 1994

Number of nodes: 1,753

Number of edges: 8,576

(B) Alliance Network in 2002

Number of nodes: 1,973

Number of edges: 8,648

(C) Alliance Network in 2010

Number of nodes: 840

Number of edges: 1,996

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 algorithm "Force Atlas 2" and the focus on central part of alliance networks. Each snapshot shows the location of top 25 central U.S. public firms listed in Table 3. The font size proportionately increases in the degree centrality (the number of direct connections) of each firm.

Appendix 1: Variable definitions

This table describes the definition of variables used in this paper. Compustat mnemonics are reported in parenthesis with bold fonts – Ex. Total Assets (**at**).

Variables	Description
Bonacich	Bonacich (1987): The sum of all direct and indirect connections. (Appendix 2)
Degree	The number of all direct connections. (Appendix 2)
Indirect	The sum of all indirect connections = Bonacich – Degree
R&D Alliance	An indicator variable which equals 1 if alliance connections are classified as R&D agreements, (cross-) licensing agreements, or (cross-) technology transfer agreements, 0 otherwise
Non-R&D Alliance	An indicator variable which equals 1 if alliance connections are classified as joint ventures, manufacturing agreements, or marketing agreements, 0 otherwise. R&D alliances are excluded from Non-R&D alliances.
Horizontal Alliance	An indicator variable which equals 1 if an alliance connects two firms operating in the same SIC 3-digit industry, 0 otherwise
CAPEX	Capital Expenditure (**capx**) / lagged Total Assets (**at**).
R&D	Research and Development Expenditure (**xrd**) / lagged Total Assets (**at**). It is set to zero if regression samples include firms with missing R&D.
Assets	Total Assets (**at**), deflated to 2009 dollars using U.S. GDP deflator from Bureau of Economic Analysis
Age	1 + the number of years appearing in Compustat
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 CRSP daily stock price at the last trading date of the fiscal year.
CF	[Income Before Extraordinary Items (**ib**) + Depreciation and Amortization Expenses (**dp**) + R&D Expenditure (**xrd**)] / Total Assets (**at**)
ROA	Operating Income Before Depreciation and Amortization (**oibdp**) / Total Assets (**at**)
Cash Holding	Cash and Short-term Investments (**che**) / Total Assets (**at**)
Leverage	[Short-term Debt (**dlc**) + Long-term Debt (**dltt**)] / Total Assets (**at**)
Asset Growth	Change in Total Assets / lagged Total Assets
Sales Growth	Change in Sales (**sale**)/ lagged Sales
PPE	Net Property, Plant and Equipment (**ppent**) / Total Assets (**at**)
Return Volatility	Standard deviation of daily stock returns. I drop measures obtained using less than 30 daily observations.
Diversification	1 – HHI of Compustat business segment sales. Segments are defined at the SIC 4-digit industry level.
WW Index	Whited and Wu (2006): -0.091 * CF – 0.062 * Dividend Payer Dummy + 0.021 * Long-term Debt (**dltt** / **at**) – 0.044 * Log(Assets) + 0.102 * Industry Sales Growth (SIC 3-digit) – 0.035 * Firm Sales Growth

Price Informativeness	Foucault and Fresard (2014): ln(1 – R^2 / R^2) where R^2 is R-square from the regression of daily stock return on market and industry (SIC 3-digit) value-weighted portfolio returns. Regressions are estimated each calendar year. I drop measures obtained using less than 30 daily observations.
PIN	Measure of Probability of Informed Trading by Brown and Hillegeist (2007). The dataset is available at http://scholar.rhsmith.umd.edu/sbrown/pin-data.
DD1Due	Almeida, Campello, Laranjeira and Weisbenner (2012): Long-term debt maturing during the first-year after the annual report (**dd1**) / Total long-term debt (**dd1** + **dltt**)
Industry Shock Index	Harford (2005): The first principal component from the seven economic shock variables: asset turnover (**sale** / **at**), capital expenditures (capex / at), employee (**emp**) growth, net profit margin (**ni** / **at**), research and development expenditures (**xrd** / **at**), return on assets (**oibdp** / **at**), and sales (**sale**) growth. Median values of variables are drawn from each year and industry (SIC 3-digit) to perform the principal component analysis.
Positive (Negative) Industry Shock	An indicator variable that equals 1 if Industry Shock belongs to top 10% (bottom 10%) of distributions, 0 otherwise
Combined Reporting	A firm-level index of combined income reporting requirement based on the geographic dispersion of firm operations. I use the score of corporate geographic footprint that is used in García and Norli (2012) to measure the firms' operating intensity for each state and fiscal year (the dataset is available at https://sites.google.com/site/financieru/resources/software. These scores are aggregated at the firm-year level by taking a weighted average with the weight of 1 or 0, depending on whether the state has adopted combined income reporting requirement or not.
Combined Reporting (HQ)	An indicator variable that equals 1 if firms are headquartered in states that have adopted combined income reporting requirement, 0 otherwise. Corporate historical headquarter information is obtained from S&P Capital IQ.

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 consisting of n nodes (members). 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 No. 3 can reach two other nodes 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 Bonacich centrality resides in that the influence of a node is determined by the strength 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 impact of each additional walk. The influence of a node then can be represented as a weighed sum of all connections emanating from the node. Denote $\boldsymbol{P}$ e as a vector of nodes' influence. $\boldsymbol{P}$ can be written as:

$$\boldsymbol{P} = \boldsymbol{G}\mathbf{1} + \beta\boldsymbol{G}^2\mathbf{1} + \beta^2\boldsymbol{G}^3\mathbf{1} + \cdots \quad \text{(A1)}$$

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

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

Bonacich centrality $\boldsymbol{C}$ is a scaled vector of the node's influence,

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

where α is a scaling parameter that allows an adjustment in the base value for each connection. For well-defined measures, any parametrization of Bonacich centrality preserves the ordinal ranking of centrality within a network.

There are other measures of network centrality popular in the existing literature, such as degree, betweenness, closeness, and eigenvector centrality. First, degree centrality measures the number of direct connections for a given node in a network. Therefore, degree centrality is equivalent to Bonacich centrality with a parametrization that assigns 1 to each direct connection and assumes zero β (no weight for indirect connections). Because degree centrality is unable to measure the effect of indirect connections existing on the network, it fits less into this paper that investigates the impact of information flows through all direct and indirect connections in the network.

Second, betweenness centrality measures the extent which a node is in the middle of shortest paths between nodes in a network. 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, closeness centrality is an average distance from a given node to all other nodes in a network. Both 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 occur in any path without being limited to the shortest paths. Thus, both measures are less appropriate for my research objectives focusing on the information flows between firms in alliance networks.

Finally, eigenvector centrality is similar to Bonacich centrality in several aspects. It is defined as:

$$\lambda \boldsymbol{E} = \boldsymbol{G}\boldsymbol{E} \tag{A4}$$

where $\boldsymbol{G}$ is an $n \times n$ adjacency matrix, $\boldsymbol{E}$ is an $n \times 1$ eigenvector, and λ is the corresponding eigenvalue. Both Bonacich and eigenvector centrality gauge the effect of direct and indirect connections, and are free from the shortest-path assumption of flows as in betweenness or closeness centrality. Eigenvector centrality is an efficient and popular workhorse for static or stable networks. For example, Ahern and Harford (2014) use eigenvector centrality to evaluate the position of an industry in static input-output networks. On the other hand, Bonacich centrality provides greater measurement flexibility with parametrization to account for substantial time-series variations in the size and density of alliance networks (Table 2 and Figure 1). In sum, Bonacich centrality best fits into my research objectives, since it effectively captures the extent of information flows in considerably time-varying networks.

My base parameter value for β in the computation of Bonacich centrality is 0.02 (Section 3.2). As a robustness check, I construct two additional measures of the Bonacich centrality using 0.01 and 0.03 as alternative values for β: "Bonacich-" and "Bonacich+". Table A1 compares the summary statistics across different centrality measures: degree, Bonacich-, Bonacich, Bonacich+, eigenvector, and betweenness centrality. All centrality values are log-transformed. Panel A shows that both the mean and standard deviation of centrality measures monotonically increase from degree centrality to Bonacich+ centrality. Notice that degree centrality assigns no weight on indirect connections while Bonacich+ centrality assigns the greatest weight. Hence, this result supports that the value of each indirect connection is increasing from zero in degree centrality to the largest in Bonacich+.

Panel B reports the correlation coefficients between the above centrality measures. It is worth noting that the correlation between degree centrality and other measures becomes lower as Bonacich centrality assigns greater weight (higher β) on indirect connections. Consequently, eigenvector centrality seems to more emphasize the impact of indirect connections. Additionally, the correlation coefficients between betwenness centrality and other centrality measures are among the lowest, reflecting that betweenness centrality relies on the shortest-path assumption that other measures do not.

Table A1

Summary of Network Centrality Measures

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

Panel A: Descriptive Statistics						
	N	Mean	Std.	P25	Median	P75
Log(Degree)	18,830	0.745	0.930	0.000	0.693	1.099
Log(Bonacich-) (β = 1%)	18,830	0.928	0.998	0.042	0.720	1.457
Log(Centrality) (β = 2%)	18,830	1.158	1.141	0.101	0.854	1.859
Log(Bonacich+) (β = 3%)	18,830	1.647	1.546	0.206	1.243	2.730
Log(Eigenvector)	18,830	-5.002	1.814	-6.502	-5.061	-3.606
Log(Betweenness)	18,830	0.002	0.007	0.000	0.000	0.001

Panel B: Correlation Matrix						
Number of Observations: 18,830						
	Degree	Bonacich-	Bonacich	Bonacich+	Eigenvector	Betweenness
Log(Degree)	1					
Log(Bonacich-) (β = 1%)	0.9750	1				
Log(Centrality) (β = 2%)	0.9180	0.9820	1			
Log(Bonacich+) (β = 3%)	0.7934	0.8984	0.9621	1		
Log(Eigenvector)	0.7195	0.8029	0.8421	0.8221	1	
Log(Betweenness)	0.5223	0.4852	0.4301	0.3302	0.3589	1

Appendix 3: State-level Adoption Status of Combined Reporting

The following table lists states that requires combined reporting for corporate income tax. *Effective* is the first tax year in which combined reporting became effective. Blank indicates that the state has yet adopted the rule of combined reporting. This table refers the following sources: i) Mazerov (2009), ii) Willson and Barnett (2014) "Combined Reporting Developments" from www.sutherland.com.

State	Effective	State	Effective	State	Effective
Alabama		Maryland		South Carolina	
Alaska	Pre-1985	Massachusetts	2009	South Dakota	
Arizona	Pre-1985	Michigan	2009	Tennessee	
Arkansas		Minnesota	Pre-1985	Texas	2008
California	Pre-1985	Mississippi		Utah	Pre-1985
Colorado		Missouri		Vermont	2006
Connecticut	2015	Montana	Pre-1985	Virginia	
District of Columbia	2011	Nebraska	Pre-1985	Washington	
Delaware		Nevada		West Virginia	2009
Florida		New Hampshire	Pre-1985	Wisconsin	2009
Georgia		New Jersey		Wyoming	
Hawaii	Pre-1985	New Mexico			
Idaho	Pre-1985	New York	2007		
Illinois	Pre-1985	North Carolina			
Indiana		North Dakota	Pre-1985		
Iowa		Ohio			
Kansas	Pre-1985	Oklahoma			
Kentucky		Oregon	Pre-1985		
Louisiana		Pennsylvania			
Maine	Pre-1985	Rhode Island	2014		

Alliance Networks, Corporate Investment, and Firm Valuation

Internet Appendix Tables

Sangho Lee

Internet Appendix Table 1

Time-series Trends in Alliance Types

This table reports time-series trends in alliance types classified by SDC. The sample consists of 16,021 alliance deals announced in 1990-2013 and formed between at least two firms in Compustat/CRSP merged (CCM) database. Alliance types are not mutually exclusive (Panel B – D of Table 1), and therefore the sum of their percentages may exceed or fall below 100%.

Year	Deals Announced	Joint Venture (%)	Licensing Agreement (%)	Manufacturing Agreement (%)	Marketing Agreement (%)	R&D Agreement (%)	Technology Transfer (%)
1990	509	40.47	15.32	20.24	28.29	15.72	15.91
1991	826	33.05	14.29	17.92	35.23	21.79	18.04
1992	1,003	17.05	17.75	15.75	54.14	39.69	15.25
1993	1,025	17.76	19.90	16.20	51.81	38.34	36.10
1994	1,136	22.98	24.82	16.20	41.29	40.67	56.60
1995	1,141	29.10	30.06	17.79	38.39	31.03	48.12
1996	868	25.35	32.60	12.33	30.99	24.54	29.15
1997	1,227	25.18	31.21	12.14	23.88	25.02	20.29
1998	1,229	17.25	29.94	13.18	18.23	9.19	17.41
1999	1,447	14.72	18.94	12.65	13.13	5.39	7.95
2000	1,272	26.89	4.64	8.41	11.95	7.00	4.40
2001	768	18.36	6.64	9.12	16.15	10.55	1.95
2002	499	14.83	7.01	12.43	23.05	13.03	3.81
2003	543	6.81	14.55	6.63	24.31	11.79	3.13
2004	409	6.85	13.69	8.07	28.12	13.69	3.42
2005	458	7.86	16.16	10.92	23.58	20.09	24.02
2006	391	12.02	11.51	12.79	17.90	14.07	28.90
2007	360	13.61	9.72	11.39	19.72	15.28	21.67
2008	278	12.95	6.48	15.83	14.75	12.95	15.83
2009	115	33.91	0.87	12.17	6.09	4.35	3.48
2010	72	50.00	1.39	6.94	4.17	11.11	2.78
2011	134	41.79	4.48	11.19	6.72	11.94	3.73
2012	181	29.28	6.63	7.18	5.53	18.23	14.37
2013	130	29.23	6.92	6.15	6.92	15.39	6.92
Total	16,021	22.80	14.40	12.23	22.68	17.95	16.80

Internet Appendix Table 2

Main Results: Controlling for Industry-Year Fixed Effects

This table examines the impact of alliance network centrality on investment-to-price sensitivity. The dependent variable is capital expenditure (*CAPEX*) in Columns (1) and (2), capital plus research and development expenditures (*CAPEX + R&D*) in Columns (3) and (4), *CAPEX + R&D* of firms with non-missing *R&D* in Columns (5) and (6), and non-missing *R&D* in Columns (7) and (8). All dependent variables are measured in percentage points. *Log(Centrality)* is the natural logarithm of the Bonacich centrality described in Section 3.2. The main independent variable is the interaction term between *Log(Centrality)* and Tobin's Q, a proxy for price-based investment opportunities. See Appendix 1 for the complete list of variable definitions. 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		CAPEX + R&D		CAPEX + R&D (non-missing)		R&D (non-missing)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Centrality)	-0.089	-0.094	2.350***	1.874***	2.935***	2.414***	2.953***	2.465***
	(-0.80)	(-0.83)	(10.36)	(8.27)	(10.70)	(8.67)	(12.16)	(9.88)
Log(Centrality) × Q	**-0.067***	**-0.068***	**-0.421*****	**-0.240*****	**-0.512*****	**-0.338*****	**-0.420*****	**-0.256*****
	(-1.73)	**(-1.66)**	**(-5.38)**	**(-2.93)**	**(-6.18)**	**(-3.81)**	**(-5.66)**	**(-3.17)**
Log(Centrality) × CF	0.182	0.217	1.806**	2.228***	2.353***	2.790***	1.630**	2.037***
	(0.50)	(0.61)	(2.30)	(2.90)	(2.77)	(3.33)	(2.15)	(2.74)
Q	0.912***	0.834***	3.131***	2.068***	3.306***	2.259***	2.441***	1.491***
	(12.11)	(8.19)	(18.91)	(9.40)	(18.32)	(9.18)	(14.19)	(6.50)
CF	2.553***	2.405***	6.559***	6.497***	5.751***	5.533***	4.141***	3.973***
	(4.28)	(4.07)	(4.50)	(4.49)	(3.49)	(3.38)	(2.67)	(2.59)
Log(Assets)	0.062	-0.030	-2.417***	-2.767***	-2.929***	-3.269***	-3.067***	-3.338***
	(1.22)	(-0.47)	(-19.75)	(-19.42)	(-19.67)	(-19.05)	(-21.80)	(-20.73)
Informativeness		-0.201***		-1.499***		-1.576***		-1.390***
		(-2.65)		(-10.34)		(-8.79)		(-8.74)
Informativeness × Q		0.005		0.358***		0.347***		0.325***
		(0.17)		(6.43)		(5.53)		(5.63)
Diversification		-2.088***		0.298		0.355		1.348
		(-2.96)		(0.27)		(0.26)		(1.02)
Diversification × Q		0.487		-1.851***		-1.746***		-2.037***
		(1.58)		(-3.18)		(-2.70)		(-3.19)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,830	18,830	18,830	18,830	13,647	13,647	13,647	13,647
Adjusted R^2	0.372	0.374	0.443	0.454	0.431	0.440	0.459	0.468

Internet Appendix Table 3

Main Results: Controlling for the Impact of Following Analysts

This table examines whether the negative relation between alliance network centrality and investment-to-price sensitivity is driven by the variation in the number of following analysts. The dependent variable is capital expenditure (*CAPEX*) in Columns (1) and (2), capital plus research and development expenditures (*CAPEX + R&D*) in Columns (3) and (4), *CAPEX + R&D* of firms with non-missing *R&D* in Columns (5) and (6), and non-missing *R&D* in Columns (7) and (8). All dependent variables are measured in percentage points. *Log(Centrality)* is the natural logarithm of the Bonacich centrality described in Section 3.2. The main independent variable is the interaction term between *Log(Centrality)* and Tobin's Q, a proxy for price-based investment opportunities. See Appendix 1 for the complete list of variable definitions. 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		CAPEX + R&D		CAPEX + R&D (non-missing)		R&D (non-missing)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Centrality)	0.147	0.134	0.672***	0.587***	0.594***	0.537**	0.779***	0.698***
	(1.28)	(1.16)	(3.37)	(2.91)	(2.73)	(2.45)	(3.94)	(3.53)
Log(Centrality) × Q	**-0.134*****	**-0.134*****	**-0.147****	**-0.118**	**-0.207*****	**-0.176****	**-0.094**	**-0.064**
	(-3.25)	**(-3.15)**	**(-2.06)**	**(-1.62)**	**(-2.59)**	**(-2.15)**	**(-1.37)**	**(-0.92)**
Log(Centrality) × CF	0.406	0.373	0.818	0.816	1.300*	1.373*	0.378	0.434
	(1.10)	(1.01)	(1.31)	(1.31)	(1.78)	(1.90)	(0.65)	(0.75)
Q	0.985***	0.910***	2.454***	1.924***	2.683***	2.142***	1.865***	1.347***
	(9.48)	(6.28)	(12.88)	(7.76)	(12.50)	(7.40)	(10.42)	(5.56)
CF	2.338***	2.326***	4.046***	4.029***	4.960***	4.901***	2.128*	2.076*
	(3.90)	(3.89)	(3.57)	(3.61)	(3.60)	(3.62)	(1.86)	(1.84)
Log(Assets)	-1.271***	-1.429***	-5.874***	-6.058***	-7.280***	-7.324***	-6.124***	-6.157***
	(-8.27)	(-9.14)	(-21.09)	(-21.47)	(-23.87)	(-23.40)	(-20.41)	(-20.40)
Log(Analyst)	0.367**	0.293*	1.538***	1.195***	2.035***	1.659***	1.708***	1.363***
	(2.26)	(1.71)	(5.58)	(4.32)	(5.97)	(4.84)	(6.08)	(4.90)
Log(Analyst) × Q	0.045	0.055	-0.291***	-0.143	-0.365***	-0.199*	-0.415***	-0.263***
	(0.95)	(1.01)	(-3.03)	(-1.41)	(-3.38)	(-1.70)	(-4.39)	(-2.63)
Informativeness		-0.271***		-0.564***		-0.382***		-0.376***
		(-3.65)		(-5.03)		(-2.81)		(-3.25)
Informativeness × Q		0.013		0.140***		0.147***		0.140***
		(0.47)		(3.10)		(2.68)		(3.05)
Diversification		0.575		4.453***		4.963***		4.243***
		(0.74)		(3.73)		(3.25)		(4.22)
Diversification × Q		-0.042		-1.615**		-1.847**		-1.623***
		(-0.10)		(-2.37)		(-2.15)		(-3.29)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,830	18,830	18,830	18,830	13,647	13,647	13,647	13,647
Within R^2	0.194	0.197	0.291	0.295	0.320	0.323	0.270	0.274

Internet Appendix Table 4

Do Financial Constraints Limit the Impact of Alliance Network Centrality? (Full Tables)

This table examines whether the impact of alliance network centrality on investment-to-price sensitivity is stronger for financially unconstrained firms than for financially constrained firms. The dependent variable is capital expenditure (*CAPEX*) in Columns (1) and (2), capital plus research and development expenditures (*CAPEX* + *R&D*) in Columns (3) and (4), *CAPEX* + *R&D* of firms with non-missing *R&D* in Columns (5) and (6), and non-missing *R&D* in Columns (7) and (8). All dependent variables are measured in percentage points. Each panel reports two sets of regression results for sub-samples of financially unconstrained or constrained firms, using the following measures of financial constraints: firm size (Panel A: *Firm Size*), availability of corporate bond rating (Panel B: *Bond Rating*), and the Whited and Wu Index (Panel C: *WW Index*). Sub-samples are double-sorted (first by the Bonacich centrality and second by the measure of financial constraints) to balance the dispersion of alliance network centrality within each sub-sample. *Log(Centrality)* is the natural logarithm of the Bonacich centrality described in Section 3.2. The main independent variable is the interaction term between *Log(Centrality)* and Tobin's Q, a proxy for price-based investment opportunities. See Appendix 1 for the complete list of variable definitions. See Table 4 for the list of winsorized variables. 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.

Panel A: Firm Size

Dependent Variable	CAPEX		CAPEX + R&D		CAPEX + R&D (non-missing)		R&D (non-missing)	
Sub-sample	Large	Small	Large	Small	Large	Small	Large	Small
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Centrality)	0.392***	-0.219	0.531***	0.429	0.798***	0.531	0.345*	0.793**
	(2.77)	(-1.25)	(2.62)	(1.13)	(3.15)	(1.27)	(1.80)	(2.27)
Log(Centrality) × Q	**-0.258*****	**-0.013**	**-0.307*****	**0.036**	**-0.354*****	**-0.030**	**-0.116**	**0.015**
	(-3.29)	**(-0.24)**	**(-2.79)**	**(0.35)**	**(-3.12)**	**(-0.26)**	**(-1.51)**	**(0.17)**
Log(Centrality) × CF	0.721	0.313	2.127	0.226	2.257	0.451	1.426*	-0.150
	(0.77)	(0.79)	(1.51)	(0.30)	(1.46)	(0.54)	(1.88)	(-0.20)
Q	1.401***	0.857***	2.127***	1.576***	2.189***	1.692***	0.900***	0.879***
	(7.59)	(6.70)	(7.81)	(6.57)	(6.85)	(6.25)	(3.28)	(3.83)
CF	3.389**	1.874***	4.644**	4.266***	6.222***	4.387***	2.800**	2.541*
	(2.45)	(2.92)	(2.44)	(3.30)	(2.72)	(2.96)	(2.03)	(1.95)
Log(Assets)	-1.283***	-1.144***	-2.562***	-7.725***	-3.074***	-9.037***	-1.951***	-8.112***
	(-5.67)	(-5.34)	(-8.66)	(-16.08)	(-8.22)	(-16.21)	(-7.98)	(-16.86)
Informativeness	-0.403***	-0.176*	-0.561***	-0.515***	-0.303**	-0.711***	-0.155*	-0.572***
	(-3.70)	(-1.91)	(-4.22)	(-3.07)	(-2.20)	(-3.39)	(-1.82)	(-3.28)
Informativeness × Q	0.033	0.008	0.107**	0.094	0.031	0.108	0.070**	0.127**
	(0.91)	(0.23)	(2.10)	(1.52)	(0.60)	(1.50)	(2.07)	(2.07)
Diversification	-0.436	2.156*	0.839	6.029***	2.124*	7.105***	1.550*	4.389**
	(-0.50)	(1.82)	(0.74)	(2.94)	(1.72)	(2.77)	(1.91)	(2.50)
Diversification × Q	0.334	-0.526	-0.504	-2.167**	-1.206**	-2.236	-1.005***	-1.785**
	(0.69)	(-0.86)	(-0.75)	(-1.98)	(-2.06)	(-1.64)	(-2.79)	(-2.22)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,414	9,416	9,414	9,416	5,972	7,675	5,972	7,675
Within R^2	0.218	0.162	0.260	0.269	0.321	0.301	0.169	0.266

Internet Appendix Table 4 (Continued)

Panel B: Bond Rating								
Dependent Variable	CAPEX		CAPEX + R&D		CAPEX + R&D (non-missing)		R&D (non-missing)	
Sub-sample	Yes	No	Yes	No	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Centrality)	0.297	-0.007	0.538**	0.634*	0.711***	0.623	0.444**	0.791**
	(1.57)	(-0.04)	(2.27)	(1.72)	(2.75)	(1.48)	(2.22)	(2.38)
Log(Centrality) × Q	**-0.279*** **	**-0.040**	**-0.377*** **	**0.038**	**-0.383*** **	**-0.018**	**-0.154**	**0.003**
	(-2.71)	**(-0.62)**	**(-2.81)**	**(0.34)**	**(-2.80)**	**(-0.14)**	**(-1.51)**	**(0.03)**
Log(Centrality) × CF	0.865	-0.136	1.409	-0.010	1.594	0.239	0.400	0.134
	(1.09)	(-0.32)	(1.36)	(-0.01)	(1.46)	(0.30)	(0.60)	(0.20)
Q	1.474***	1.116***	2.274***	1.614***	2.301***	1.669***	0.991**	0.796***
	(4.74)	(6.99)	(5.41)	(6.51)	(5.07)	(5.75)	(2.35)	(3.34)
CF	3.746**	3.186***	4.971**	5.400***	6.185***	5.196***	2.789*	2.020
	(2.28)	(4.22)	(2.48)	(4.07)	(2.65)	(3.23)	(1.85)	(1.46)
Log(Assets)	-1.574***	-1.104***	-2.599***	-7.231***	-2.730***	-8.581***	-1.664***	-7.624***
	(-5.20)	(-5.14)	(-7.27)	(-17.03)	(-6.82)	(-17.24)	(-5.58)	(-17.52)
Informativeness	-0.408***	-0.181*	-0.531***	-0.768***	-0.172	-0.946***	-0.150*	-0.749***
	(-3.11)	(-1.66)	(-3.41)	(-4.69)	(-1.28)	(-4.54)	(-1.76)	(-4.41)
Informativeness × Q	0.034	-0.027	0.082	0.179***	-0.010	0.188**	0.055	0.224***
	(0.81)	(-0.66)	(1.45)	(2.83)	(-0.18)	(2.50)	(1.51)	(3.66)
Diversification	-0.818	2.745**	-0.397	6.485***	1.126	6.989**	0.690	4.673***
	(-0.89)	(1.96)	(-0.35)	(2.87)	(1.00)	(2.43)	(0.85)	(2.71)
Diversification × Q	0.623	-0.909	0.292	-3.157**	-0.588	-3.287*	-0.615	-2.704***
	(1.17)	(-1.14)	(0.41)	(-2.41)	(-1.08)	(-1.96)	(-1.61)	(-3.22)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,874	8,859	6,874	8,859	4,179	6,729	4,179	6,729
Within R^2	0.226	0.172	0.241	0.316	0.294	0.361	0.122	0.326

Continued…

Internet Appendix Table 4 (Continued)

Panel C: WW Index								
Dependent Variable	CAPEX		CAPEX + R&D		CAPEX + R&D (non-missing)		R&D (non-missing)	
Sub-sample	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)	Low (7)	High (8)
Log(Centrality)	0.262*	-0.048	0.381*	0.786**	0.637**	0.853**	0.364*	0.930***
	(1.74)	(-0.29)	(1.79)	(2.28)	(2.53)	(2.22)	(1.86)	(2.80)
Log(Centrality) × Q	**-0.278*** **	**-0.011**	**-0.371*** **	**-0.010**	**-0.438*** **	**-0.080**	**-0.170** **	**-0.021**
	(-4.53)	**(-0.20)**	**(-4.09)**	**(-0.11)**	**(-4.51)**	**(-0.73)**	**(-2.17)**	**(-0.22)**
Log(Centrality) × CF	1.833**	0.022	3.979***	-0.269	4.196***	-0.107	2.112**	-0.575
	(2.32)	(0.06)	(3.46)	(-0.38)	(3.15)	(-0.13)	(2.19)	(-0.82)
Q	1.404***	0.835***	2.284***	1.583***	2.442***	1.645***	1.073***	0.869***
	(8.52)	(6.58)	(9.04)	(6.73)	(8.41)	(6.06)	(4.24)	(3.66)
CF	2.442*	2.614***	2.337	5.436***	4.193	5.566***	1.710	3.333***
	(1.67)	(4.20)	(1.07)	(4.42)	(1.52)	(3.89)	(0.78)	(2.66)
Log(Assets)	-1.179***	-1.119***	-2.780***	-7.611***	-3.432***	-8.777***	-2.521***	-7.859***
	(-5.45)	(-5.40)	(-9.11)	(-17.14)	(-9.02)	(-16.88)	(-7.61)	(-17.62)
Informativeness	-0.350***	-0.212**	-0.623***	-0.582***	-0.391**	-0.784***	-0.305**	-0.589***
	(-3.14)	(-2.32)	(-4.10)	(-3.60)	(-2.34)	(-3.84)	(-2.35)	(-3.39)
Informativeness × Q	0.039	0.004	0.163***	0.109*	0.105	0.135*	0.134**	0.146**
	(1.12)	(0.13)	(2.71)	(1.78)	(1.64)	(1.87)	(2.53)	(2.37)
Diversification	-0.403	1.881*	1.669	4.797**	2.948***	6.187***	2.443***	3.656**
	(-0.49)	(1.87)	(1.55)	(2.54)	(2.59)	(2.67)	(3.05)	(2.11)
Diversification × Q	0.473	-0.568	-0.525	-2.316**	-1.177**	-2.352**	-1.114***	-1.925**
	(1.04)	(-1.25)	(-0.84)	(-2.43)	(-2.20)	(-2.01)	(-3.30)	(-2.37)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,404	9,426	9,404	9,426	6,021	7,626	6,021	7,626
Within R^2	0.233	0.160	0.287	0.285	0.355	0.315	0.196	0.281

Internet Appendix Table 5

Endogeneity: Controlling for the Influence of Alliance Initiation with the Cash Flow Interaction

This table addresses the endogeneity issues in alliance network centrality by controlling for the firm-year observations with new alliances in two different approaches. The first method is to control for firm-cohort fixed effects (Firm-Cohort FE) that assigns a firm-cohort dummy for each firm-year observation with new alliances, thereby relying on the within-firm variations of alliance network centrality without new alliances. The second method is to examine the impact of indirectly connected parts of alliance network centrality using a sample of firm-year observations experiencing no changes in their direct alliance connections. The dependent variable is capital expenditure (*CAPEX*) in Columns (1) and (5), capital plus research and development expenditures (*CAPEX + R&D*) in Columns (2) and (6), *CAPEX + R&D* of firms with non-missing *R&D* in Columns (3) and (7), and non-missing *R&D* in Columns (4) and (8). All dependent variables are measured in percentage points. *Log(Centrality)* is a natural logarithm of the Bonacich centrality described in Section 3.2. *Log(Degree)* is the natural logarithm of the degree centrality that equals the number of direct connections. *Log(Indirect + 1)* is one plus the natural logarithm of the indirect centrality that equals the difference between Bonacich and degree centrality. The main independent variable is the interaction term between *Log(Centrality)* (Columns 1 – 4) or *Log(Indirect + 1)* (Columns 5 – 8) and Tobin's Q, a proxy for price-based investment opportunities. See Appendix 1 for the complete list of variable definitions. See Table 4 for the list of winsorized variables. 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	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Centrality)	-0.030	0.360	0.730**	0.678**				
	(-0.18)	(1.21)	(2.03)	(2.34)				
Log(Centrality) × Q	**-0.042**	**-0.108**	**-0.184**	**-0.130**				
	(-0.72)	**(-1.03)**	**(-1.57)**	**(-1.35)**				
Log(Centrality) × CF	-0.380	-1.580**	-1.822**	-1.642**				
	(-1.18)	(-2.40)	(-2.34)	(-2.49)				
Log(Indirect + 1)					0.578*	1.154**	0.996	0.849*
					(1.88)	(2.15)	(1.49)	(1.69)
Log(Indirect + 1) × Q					**-0.262****	**-0.325***	**-0.246**	**-0.138**
					(-2.43)	**(-1.67)**	**(-1.18)**	**(-0.83)**
Log(Indirect + 1) × CF					0.671	-0.076	0.086	-1.001
					(1.09)	(-0.05)	(0.05)	(-0.61)

Continued…

Internet Appendix Table 5 (Continued)

Log(Degree)					-0.345	-0.114	0.371	0.288
					(-0.85)	(-0.17)	(0.45)	(0.41)
Log(Degree) × Q					0.280	0.329	0.034	0.100
					(1.38)	(1.08)	(0.10)	(0.35)
Log(Degree) × CF					-2.254	-2.181	-1.551	-0.708
					(-1.58)	(-0.89)	(-0.59)	(-0.30)
Q	0.979***	1.576***	1.646***	0.818***	1.031***	1.680***	1.726***	0.874***
	(8.87)	(8.12)	(7.19)	(4.02)	(7.62)	(6.77)	(5.88)	(3.21)
CF	3.198***	5.641***	5.785***	2.788**	2.628***	3.178***	3.733**	1.467
	(6.33)	(5.48)	(4.52)	(2.57)	(4.11)	(2.62)	(2.50)	(1.16)
Log(Assets)	-2.364***	-8.412***	-10.313***	-8.279***	-1.191***	-5.292***	-6.982***	-5.800***
	(-10.90)	(-19.93)	(-19.56)	(-17.93)	(-5.13)	(-12.23)	(-12.88)	(-13.48)
Informativeness	-0.083	-0.332***	-0.473***	-0.371***	-0.111	-0.411***	-0.460**	-0.342*
	(-1.08)	(-2.80)	(-3.11)	(-2.97)	(-1.22)	(-2.68)	(-2.23)	(-1.95)
Informativeness × Q	-0.047	0.071	0.076	0.129***	-0.038	0.099	0.073	0.117
	(-1.54)	(1.49)	(1.36)	(2.64)	(-0.95)	(1.44)	(0.89)	(1.56)
Diversification	1.415*	4.322***	4.836***	3.593***	-0.108	2.038	2.329	2.593*
	(1.80)	(3.27)	(2.91)	(3.06)	(-0.08)	(1.02)	(0.83)	(1.92)
Diversification × Q	-0.208	-1.297*	-1.006	-0.989*	0.352	-0.586	-0.422	-1.169*
	(-0.54)	(-1.87)	(-1.18)	(-1.73)	(0.44)	(-0.49)	(-0.25)	(-1.65)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Firm-Cohort FE	Yes	Yes	Yes	Yes	No	No	No	No
Observations	18,830	18,830	13,647	13,647	8,346	8,346	5,827	5,827
Within R^2	0.136	0.234	0.280	0.246	0.146	0.227	0.272	0.226

Internet Appendix Table 6

Self-selection: Heckman Model with Alternative Indices of Combined Reporting Index

This table examines self-selection issues regarding the choice of participating in alliance networks using Heckman two-step procedure of sample selection model. The first stage estimates a Probit regression model in which the dependent variable is an indicator variable that equals 1 if a firm is inside alliance network, 0 otherwise (Columns 1 and 4). The instrument is *Combined Reporting* that is a firm-level index of combined income reporting requirement based on corporate historical headquarter locations from S&P Capital IQ (Panel A) or corporate subsidiaries dataset used in Bodnaruk, Massa and Simonov (2013) (Panel B). The second stage estimates an OLS regression model in which the dependent variable is capital expenditure (*CAPEX*) in Column (2), capital plus research and development expenditures (*CAPEX + R&D*) in Column (3), *CAPEX + R&D* of firms with non-missing *R&D* in Column (5), and non-missing *R&D* in Column (6). All dependent variables are measured in percentage points. *Log(Centrality)* is the natural logarithm of the Bonacich centrality described in Section 3.2. The main independent variable is the interaction term between *Log(Centrality)* and Tobin's Q, a proxy for price-based investment opportunities. See Appendix 1 for the complete list of variable definitions. See Table 4 for the list of winsorized variables. 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.

Panel A: Combined Reporting Index Based on Corporate Historical Headquarter Locations						
Estimation	1st Stage	2nd Stage		1st Stage	2nd Stage	
Dependent Variable	Inside Network?	CAPEX	CAPEX + R&D	Inside Network?	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Centrality)		-0.041	1.882***		2.528***	2.442***
		(-0.55)	(12.89)		(13.76)	(15.01)
Log(Centrality) × Q		**-0.080*** **	**-0.193*** **		**-0.330*** **	**-0.223*** **
		(-3.91)	**(-4.69)**		**(-6.98)**	**(-5.32)**
Log(Centrality) × CF		0.367*	2.829***		3.456***	2.381***
		(1.68)	(6.65)		(6.87)	(5.35)
Q	0.010*	0.894***	1.993***	0.004	2.324***	1.429***
	(1.71)	(17.26)	(18.47)	(0.56)	(18.56)	(12.86)
CF	-0.470***	2.295***	9.084***	-0.403***	7.345***	5.744***
	(-12.49)	(5.84)	(11.32)	(-9.36)	(7.95)	(7.02)
Log(Assets)	0.296***	0.079	-4.758***	0.292***	-4.989***	-4.827***
	(56.49)	(0.75)	(-21.32)	(44.25)	(-20.25)	(-22.07)
Informativeness	-0.081***	-0.217***	-0.624***	-0.084***	-0.754***	-0.718***
	(-13.20)	(-3.80)	(-5.16)	(-10.51)	(-4.92)	(-5.28)
Informativeness × Q	0.015***	0.002	0.195***	0.014***	0.194***	0.220***
	(7.65)	(0.16)	(6.08)	(6.20)	(5.32)	(6.78)
Diversification	-0.040	-1.884***	0.907	-0.087	0.884	2.166**
	(-0.65)	(-4.59)	(1.02)	(-1.13)	(0.79)	(2.17)
Diversification × Q	0.155***	0.538***	-2.705***	0.173***	-2.514***	-2.735***
	(5.33)	(3.02)	(-6.82)	(5.03)	(-5.48)	(-6.70)
Combined Reporting	**0.110*** **			**0.133*** **		
	(8.31)			**(8.26)**		
Inverse Mills Ratio		0.846	-11.737***		-11.263***	-12.140***
		(1.55)	(-10.27)		(-8.66)	(-10.22)

Continued…

Internet Appendix Table 6 (Continued)

Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57,419	18,298	18,298	36,125	13,064	13,064

Panel B: Combined Reporting Index Based on Corporate Subsidiary Locations						
Estimation	1st Stage	2nd Stage		1st Stage	2nd Stage	
Dependent Variable	Inside Network?	CAPEX	CAPEX + R&D	Inside Network?	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Centrality)		0.073	1.777***		2.189***	1.994***
		(0.75)	(10.69)		(10.46)	(11.10)
Log(Centrality) × Q		**-0.151*** **	**-0.291*** **		**-0.424*** **	**-0.234*** **
		(-5.53)	**(-6.26)**		**(-7.77)**	**(-5.01)**
Log(Centrality) × CF		-0.414	0.901		1.988***	1.432**
		(-1.28)	(1.64)		(3.06)	(2.57)
Q	-0.003	1.108***	2.321***	-0.001	2.536***	1.436***
	(-0.28)	(14.56)	(17.83)	(-0.04)	(16.19)	(10.67)
CF	-0.402***	2.601***	8.219***	-0.377***	6.160***	4.904***
	(-5.49)	(3.97)	(7.37)	(-4.48)	(4.59)	(4.26)
Log(Assets)	0.353***	0.190	-3.113***	0.328***	-3.182***	-3.215***
	(36.41)	(1.35)	(-12.84)	(26.66)	(-11.56)	(-13.58)
Informativeness	-0.085***	-0.262***	-0.852***	-0.086***	-1.025***	-0.939***
	(-8.16)	(-3.33)	(-6.32)	(-6.22)	(-5.70)	(-6.07)
Informativeness × Q	0.014***	0.043**	0.248***	0.010**	0.262***	0.242***
	(3.95)	(1.98)	(6.63)	(2.43)	(5.93)	(6.37)
Diversification	-0.055	-1.545***	1.354	0.122	0.646	1.456
	(-0.57)	(-2.85)	(1.45)	(0.98)	(0.54)	(1.42)
Diversification × Q	0.173***	0.269	-2.194***	0.130**	-1.801***	-1.851***
	(3.83)	(1.22)	(-5.76)	(2.42)	(-4.10)	(-4.90)
Combined Reporting	**0.078*** **			**0.094*** **		
	(3.05)			**(3.03)**		
Inverse Mills Ratio		1.469**	-4.266***		-3.197**	-2.994**
		(2.21)	(-3.74)		(-2.20)	(-2.39)
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,363	13,252	13,252	11,795	9,846	9,846

Internet Appendix Table 7

Robustness Tests (Full Tables)

This table tests the robustness of the negative relation between alliance network centrality and investment-to-price sensitivity. The dependent variable is capital expenditure (*CAPEX*) in Column (1), capital plus research and development expenditures (*CAPEX* + *R&D*) in Column (2), *CAPEX* + *R&D* of firms with non-missing *R&D* in Column (3), and non-missing *R&D* in Column (4). All dependent variables are measured in percentage points. Specifications (1) – (7) use alternative settings of investment regressions. Specification (1) estimates the cumulant estimator of Erickson, Jiang and Whited (2014) that provides unbiased estimates of coefficients in errors-in-variables panel regressions. Specification (2) uses Total Q (Peters and Taylor 2017) that incorporates both tangible and intangible capital in estimating firms' total capital to measure price-based investment opportunities. Specification (3) uses a value-weighted industry-level (SIC 3-digit) Tobin's Q to measure price-based investment opportunities. Specification (4) includes the square-term of Tobin's Q to control for the potential non-linearity in investment-to-price sensitivity. Specification (5) controls for additional set of firm characteristics that may affect investment decisions: firm age, sales growth, book leverage, and cash holding. Specification (6) excludes firms experiencing more than 20% of changes in total assets to isolate the impact of firms with ongoing material changes in operations. Specification (7) reports the cross-sectional differences in the impact of alliance network centrality on investment-to-price sensitivity by estimating Fama-MacBeth regressions (Fama and MacBeth 1973). Specifically, the reported coefficients are the average of cross-sectional coefficients estimated each alliance network between 1994 and 2013 with industry (SIC 3-digit) fixed effects. Specifications (8) – (11) test alternative assumptions for the construction of alliance networks. Specifications (8) and (9) test the robustness of results for alternative assumptions on alliance duration: 3- and 7-year (see Section 2.1). Specification (10) uses centrality measures constructed from alliance networks consisting of alliance deals involving at least two U.S. firms in Compustat/CRSP merged database. Specification (11) uses centrality measures constructed from alliance networks consisting of entire global alliance deals involving not only firms but also universities, government agencies, and other institutions. Specifications (12) – (16) test the robustness of results for alternative measures of network centrality. Specification (12) uses degree centrality that only counts the impact of direct connections. Specifications (13) and (14) use alternative parameter choices for the calculation of Bonacich centrality. Specifications (15) and (16) check the robustness of results using eigenvector and betweenness centrality. See Section 3.2 and Appendix 2 for more detail on various measures of network centrality. The main independent variable is the interaction term between *Log(Centrality)* and Tobin's Q, a proxy for price-based investment opportunities. See Appendix 1 for the complete list of variable definitions. See Table 4 for the list of winsorized variables. 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.

Continued…

Internet Appendix Table 7 (Continued)

Specification (1) Cumulant Estimator (Erickson, Jiang and Whited 2014)				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Centrality)	4.759***	4.977***	5.940***	7.286***
	(7.51)	(6.83)	(6.28)	(4.39)
Log(Centrality) × Q	**-1.982*****	**-2.105*****	**-2.404*****	**-3.061*****
	(-6.95)	**(-6.52)**	**(-6.29)**	**(-4.50)**
Log(Centrality) × CF	3.558***	3.960***	4.111***	4.369***
	(4.77)	(3.98)	(3.80)	(3.03)
Q	5.789***	7.389***	8.294***	9.609***
	(9.34)	(9.52)	(8.59)	(5.44)
CF	-2.649**	-2.404	-2.619	-8.616***
	(-2.08)	(-1.43)	(-1.32)	(-2.95)
Log(Assets)	-0.618**	-3.773***	-4.449***	-2.259***
	(-2.49)	(-11.18)	(-10.32)	(-3.78)
Firm FE (de-meaned)	Yes	Yes	Yes	Yes
Observations	18,830	18,830	13,647	13,647

Continued…

Specification (2) Total Q (Peters and Taylor 2017)				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Centrality)	0.081	0.597***	0.693***	0.651***
	(0.84)	(3.45)	(3.22)	(3.75)
Log(Centrality) × Q	**-0.094*****	**-0.113*****	**-0.171*****	**-0.066***
	(-3.20)	**(-2.58)**	**(-3.52)**	**(-1.74)**
Log(Centrality) × CF	0.526	1.038	1.342*	0.454
	(1.38)	(1.58)	(1.81)	(0.76)
Q	0.559***	0.715***	0.821***	0.265**
	(8.51)	(6.61)	(6.31)	(2.50)
CF	2.303***	4.419***	4.670***	2.625**
	(3.74)	(3.75)	(3.30)	(2.22)
Log(Assets)	-1.789***	-6.868***	-8.154***	-6.656***
	(-12.42)	(-23.45)	(-22.71)	(-21.38)
Informativeness	-0.348***	-0.523***	-0.519***	-0.253***
	(-6.53)	(-6.24)	(-4.75)	(-2.82)
Informativeness × Q	0.025	0.039	0.021	0.018
	(1.54)	(1.30)	(0.59)	(0.62)
Diversification	0.614	1.879***	2.194**	1.477**
	(1.35)	(2.62)	(2.40)	(2.01)
Diversification × Q	-0.050	-0.385	-0.416	-0.360
	(-0.17)	(-0.92)	(-0.82)	(-1.42)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	18,830	18,830	13,647	13,647
Within R^2	0.186	0.249	0.288	0.230

Continued…

Specification (3) Industry Q				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Centrality)	0.145	0.753***	1.020***	0.913***
	(0.97)	(3.14)	(3.36)	(3.88)
Log(Centrality) × Q	**-0.154*** **	**-0.212** **	**-0.310*** **	**-0.155* **
	(-3.11)	**(-2.47)**	**(-2.98)**	**(-1.88)**
Log(Centrality) × CF	0.471	1.103*	1.333*	0.530
	(1.32)	(1.79)	(1.95)	(0.96)
Q	0.654***	0.681***	0.683**	0.058
	(4.87)	(2.91)	(2.40)	(0.25)
CF	2.832***	4.679***	4.903***	2.329**
	(4.73)	(4.20)	(3.72)	(2.11)
Log(Assets)	-1.516***	-6.198***	-7.342***	-6.109***
	(-10.11)	(-22.49)	(-21.96)	(-21.22)
Informativeness	-0.772***	-1.581***	-1.764***	-1.082***
	(-12.95)	(-15.18)	(-13.29)	(-9.76)
Informativeness × Q	0.176***	0.482***	0.506***	0.367***
	(9.07)	(12.70)	(11.76)	(10.49)
Diversification	-1.020	1.395	2.182	2.643***
	(-1.25)	(1.18)	(1.49)	(2.79)
Diversification × Q	0.648	-0.278	-0.520	-0.936**
	(1.51)	(-0.41)	(-0.62)	(-2.01)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	18,830	18,830	13,647	13,647
Within R^2	0.175	0.273	0.315	0.265

Continued…

Internet Appendix Table 7 (Continued)

Specification (4) Non-linearity: Controlling for Q^2				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Centrality)	0.082	0.637***	0.899***	0.837***
	(0.71)	(3.18)	(3.77)	(4.27)
Log(Centrality) × Q	**-0.103****	**-0.124***	**-0.225*****	**-0.108***
	(-2.47)	**(-1.79)**	**(-2.96)**	**(-1.71)**
Log(Centrality) × CF	0.326	0.732	1.083	0.398
	(0.88)	(1.17)	(1.54)	(0.69)
Q	1.751***	2.187***	2.139***	0.598**
	(10.64)	(7.42)	(6.31)	(2.10)
CF	2.018***	3.671***	3.803***	1.975*
	(3.41)	(3.30)	(2.87)	(1.74)
Log(Assets)	-1.217***	-5.696***	-6.856***	-5.890***
	(-8.43)	(-20.56)	(-20.38)	(-20.22)
Informativeness	-0.220***	-0.650***	-0.682***	-0.578***
	(-3.17)	(-5.72)	(-4.74)	(-4.71)
Informativeness × Q	-0.003	0.174***	0.174***	0.208***
	(-0.13)	(3.99)	(3.41)	(4.67)
Diversification	0.943	4.593***	5.323***	4.017***
	(1.17)	(3.76)	(3.48)	(4.00)
Diversification × Q	-0.241	-1.726**	-1.877**	-1.535***
	(-0.55)	(-2.49)	(-2.20)	(-3.12)
Q^2	-0.073***	-0.053**	-0.033	0.023
	(-4.86)	(-2.03)	(-1.11)	(0.96)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	18,830	18,830	13,647	13,647
Within R^2	0.199	0.294	0.335	0.272

Continued…

Internet Appendix Table 7 (Continued)

Specification (5) More Controls: Age, Sales Growth, Leverage, and Cash				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Centrality)	0.214*	0.771***	1.023***	0.855***
	(1.88)	(3.94)	(4.40)	(4.44)
Log(Centrality) × Q	**-0.129*****	**-0.148****	**-0.239*****	**-0.106***
	(-3.19)	**(-2.22)**	**(-3.24)**	**(-1.70)**
Log(Centrality) × CF	0.509	0.974	1.239*	0.432
	(1.39)	(1.58)	(1.79)	(0.75)
Q	1.011***	1.665***	1.810***	0.858***
	(10.82)	(9.72)	(9.18)	(4.91)
CF	1.461**	2.740**	3.163**	1.727
	(2.49)	(2.45)	(2.42)	(1.56)
Log(Assets)	-1.187***	-5.617***	-6.809***	-5.878***
	(-8.04)	(-20.10)	(-19.95)	(-19.75)
Informativeness	-0.197***	-0.603***	-0.649***	-0.556***
	(-2.87)	(-5.36)	(-4.50)	(-4.52)
Informativeness × Q	-0.015	0.158***	0.163***	0.203***
	(-0.65)	(3.65)	(3.19)	(4.55)
Diversification	0.701	4.534***	5.328***	4.169***
	(0.92)	(3.83)	(3.59)	(4.13)
Diversification × Q	-0.067	-1.631**	-1.827**	-1.595***
	(-0.16)	(-2.41)	(-2.20)	(-3.22)
Log(Age)	-1.259***	-1.848***	-1.637**	-0.813
	(-3.25)	(-2.83)	(-2.05)	(-1.23)
Sales Growth	0.197***	0.080	0.096	-0.055
	(2.63)	(0.48)	(0.50)	(-0.33)
Leverage	-4.425***	-6.340***	-5.192***	-1.455
	(-6.56)	(-5.64)	(-3.96)	(-1.30)
Cash Holding	0.073	-1.172	-1.986	-2.080**
	(0.13)	(-1.07)	(-1.60)	(-1.97)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	18,830	18,830	13,647	13,647
Within R^2	0.208	0.301	0.339	0.273

Continued…

Internet Appendix Table 7 (Continued)

Specification (6) Excluding Firms with More than 20% of Asset Changes				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Centrality)	0.104	0.575***	1.060***	0.892***
	(0.99)	(3.13)	(4.69)	(4.68)
Log(Centrality) × Q	**-0.067***	**-0.075**	**-0.190****	**-0.115***
	(-1.89)	**(-1.01)**	**(-2.24)**	**(-1.68)**
Log(Centrality) × CF	0.480	0.528	0.142	-0.269
	(1.48)	(0.84)	(0.19)	(-0.42)
Q	0.604***	0.925***	1.134***	0.518**
	(6.62)	(4.83)	(4.82)	(2.55)
CF	2.441***	4.207***	5.655***	3.242**
	(3.83)	(3.24)	(3.45)	(2.28)
Log(Assets)	-0.189	-3.242***	-4.368***	-4.208***
	(-1.44)	(-10.35)	(-11.67)	(-11.60)
Informativeness	-0.155**	-0.498***	-0.431***	-0.378***
	(-2.38)	(-4.32)	(-2.91)	(-2.98)
Informativeness × Q	-0.035	0.116**	0.094	0.146**
	(-1.43)	(2.06)	(1.36)	(2.36)
Diversification	-0.662	1.776*	2.780**	2.561***
	(-0.91)	(1.78)	(2.29)	(3.46)
Diversification × Q	0.511	-0.467	-0.553	-0.918**
	(1.23)	(-0.80)	(-0.80)	(-2.56)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	11,987	11,987	8,410	8,410
Within R^2	0.149	0.184	0.222	0.180

Continued…

Internet Appendix Table 7 (Continued)

Specification (7) Fama-MacBeth Regressions				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Centrality)	-0.210*	1.852***	2.471***	2.699***
	(-1.90)	(6.00)	(5.65)	(6.72)
Log(Centrality) × Q	**-0.066**	**-0.104**	**-0.300***	**-0.275****
	(-1.54)	**(-1.06)**	**(-1.96)**	**(-2.12)**
Log(Centrality) × CF	0.668	2.005***	3.114***	2.290***
	(0.89)	(2.91)	(2.99)	(3.54)
Q	0.731***	1.912***	2.078***	1.533***
	(12.20)	(10.15)	(7.95)	(6.87)
CF	2.741***	8.509***	7.194***	5.129***
	(3.08)	(8.83)	(7.73)	(4.20)
Log(Assets)	-0.023	-2.770***	-3.242***	-3.329***
	(-0.43)	(-22.54)	(-24.57)	(-27.71)
Informativeness	-2.337***	-0.584	-0.828	0.307
	(-3.81)	(-0.67)	(-0.65)	(0.26)
Informativeness × Q	0.828**	-1.156*	-0.725	-1.284
	(2.65)	(-1.91)	(-0.76)	(-1.47)
Diversification	-0.080	-1.523***	-1.583***	-1.466***
	(-1.15)	(-18.24)	(-9.52)	(-17.85)
Diversification × Q	-0.016	0.421***	0.454***	0.397***
	(-0.75)	(9.54)	(8.03)	(8.93)
Industry FE	Yes	Yes	Yes	Yes
Observations	18,830	18,830	13,647	13,647

Continued…

Internet Appendix Table 7 (Continued)

Specification (8) 3-year Alliance Duration				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Centrality)	0.302**	0.951***	1.251***	0.960***
	(2.40)	(4.31)	(4.76)	(4.40)
Log(Centrality) × Q	**-0.126*** **	**-0.146* **	**-0.245*** **	**-0.110**
	(-2.59)	**(-1.89)**	**(-2.92)**	**(-1.56)**
Log(Centrality) × CF	0.446	1.126	1.480	0.854
	(0.91)	(1.37)	(1.60)	(1.13)
Q	0.925***	1.487***	1.660***	0.722***
	(9.22)	(8.59)	(8.43)	(4.28)
CF	2.566***	4.607***	4.740***	2.090*
	(3.77)	(3.78)	(3.28)	(1.69)
Log(Assets)	-1.492***	-6.143***	-7.140***	-6.002***
	(-8.69)	(-20.30)	(-19.28)	(-18.44)
Informativeness	-0.320***	-0.811***	-0.796***	-0.667***
	(-3.76)	(-6.34)	(-5.01)	(-4.98)
Informativeness × Q	0.023	0.224***	0.217***	0.245***
	(0.85)	(4.69)	(3.93)	(5.07)
Diversification	0.468	4.814***	6.070***	4.711***
	(0.58)	(3.91)	(4.07)	(4.20)
Diversification × Q	-0.138	-2.017***	-2.517***	-1.898***
	(-0.33)	(-2.92)	(-3.19)	(-3.54)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	14,816	14,816	10,838	10,838
Within R^2	0.207	0.320	0.360	0.291

Continued…

Internet Appendix Table 7 (Continued)

Specification (9) 7-year Alliance Duration				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Centrality)	0.032	0.517***	0.731***	0.701***
	(0.29)	(2.75)	(3.15)	(3.60)
Log(Centrality) × Q	**-0.114*****	**-0.120***	**-0.196*****	**-0.078**
	(-3.11)	**(-1.93)**	**(-2.83)**	**(-1.33)**
Log(Centrality) × CF	0.181	0.313	0.585	0.141
	(0.59)	(0.59)	(0.95)	(0.28)
Q	1.023***	1.638***	1.746***	0.787***
	(10.95)	(9.63)	(8.90)	(4.55)
CF	2.856***	5.046***	5.193***	2.686**
	(5.02)	(4.88)	(4.18)	(2.51)
Log(Assets)	-1.169***	-5.433***	-6.617***	-5.700***
	(-8.84)	(-20.79)	(-20.66)	(-20.71)
Informativeness	-0.248***	-0.676***	-0.745***	-0.579***
	(-3.92)	(-6.39)	(-5.53)	(-5.03)
Informativeness × Q	-0.010	0.168***	0.174***	0.207***
	(-0.48)	(4.05)	(3.56)	(4.86)
Diversification	0.141	3.740***	4.573***	3.931***
	(0.20)	(3.36)	(3.24)	(4.07)
Diversification × Q	0.023	-1.409**	-1.550**	-1.367***
	(0.06)	(-2.23)	(-1.99)	(-2.75)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	21,365	21,365	15,416	15,416
Within R^2	0.185	0.276	0.317	0.256

Continued…

Internet Appendix Table 7 (Continued)

Specification (10) Within U.S. Networks				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Centrality)	0.067	0.628***	0.885***	0.872***
	(0.55)	(2.85)	(3.34)	(3.86)
Log(Centrality) × Q	**-0.107****	**-0.128***	**-0.214*****	**-0.113**
	(-2.40)	**(-1.71)**	**(-2.61)**	**(-1.59)**
Log(Centrality) × CF	0.420	1.020	1.375	0.605
	(0.98)	(1.32)	(1.53)	(0.82)
Q	0.970***	1.595***	1.703***	0.825***
	(10.24)	(9.18)	(8.55)	(4.61)
CF	2.227***	3.533***	3.516**	1.534
	(3.64)	(3.05)	(2.51)	(1.27)
Log(Assets)	-1.316***	-5.801***	-6.980***	-5.937***
	(-8.46)	(-20.10)	(-19.98)	(-19.56)
Informativeness	-0.272***	-0.625***	-0.646***	-0.476***
	(-3.79)	(-5.43)	(-4.44)	(-3.84)
Informativeness × Q	0.001	0.161***	0.165***	0.189***
	(0.03)	(3.62)	(3.15)	(4.09)
Diversification	0.839	4.661***	5.645***	4.195***
	(1.16)	(4.06)	(4.02)	(3.96)
Diversification × Q	-0.252	-1.781***	-2.125***	-1.575***
	(-0.66)	(-2.77)	(-2.79)	(-3.05)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	17,253	17,253	12,467	12,467
Within R^2	0.200	0.295	0.337	0.272

Continued…

Internet Appendix Table 7 (Continued)

Specification (11) Entire Global Networks				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Centrality)	0.042	0.424***	0.593***	0.524***
	(0.64)	(3.78)	(4.40)	(4.66)
Log(Centrality) × Q	**-0.076*****	**-0.102****	**-0.157*****	**-0.072***
	(-3.19)	**(-2.57)**	**(-3.55)**	**(-1.91)**
Log(Centrality) × CF	0.360*	0.754**	0.701*	0.208
	(1.96)	(2.30)	(1.87)	(0.65)
Q	1.016***	1.744***	1.860***	0.890***
	(12.38)	(12.61)	(11.52)	(6.56)
CF	2.290***	2.909***	3.498***	1.436
	(4.71)	(3.21)	(3.20)	(1.51)
Log(Assets)	-1.261***	-5.378***	-6.649***	-5.638***
	(-10.86)	(-23.58)	(-23.26)	(-22.25)
Informativeness	-0.219***	-0.643***	-0.690***	-0.555***
	(-4.24)	(-7.83)	(-6.48)	(-6.25)
Informativeness × Q	-0.004	0.155***	0.153***	0.177***
	(-0.19)	(4.60)	(3.75)	(5.03)
Diversification	0.118	3.589***	4.145***	3.842***
	(0.21)	(4.03)	(3.68)	(4.83)
Diversification × Q	-0.085	-1.483***	-1.587**	-1.368***
	(-0.25)	(-2.71)	(-2.37)	(-3.25)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	30,423	30,423	21,470	21,470
Within R^2	0.173	0.260	0.300	0.240

Continued…

Internet Appendix Table 7 (Continued)

Specification (12) Bonacich- Centrality (β = 0.01)				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Bonacich-)	0.114	0.667***	0.940***	0.839***
	(0.89)	(2.99)	(3.49)	(3.73)
Log(Bonacich-) × Q	**-0.134***	**-0.138***	**-0.241***	**-0.095**
	(-2.75)	**(-1.75)**	**(-2.77)**	**(-1.29)**
Log(Bonacich-) × CF	0.274	0.894	1.308	0.672
	(0.61)	(1.19)	(1.57)	(1.00)
Q	1.009***	1.617***	1.739***	0.786***
	(10.69)	(9.66)	(9.02)	(4.63)
CF	2.480***	3.956***	4.041***	1.697
	(4.38)	(3.73)	(3.23)	(1.61)
Log(Assets)	-1.263***	-5.725***	-6.869***	-5.868***
	(-8.66)	(-20.66)	(-20.40)	(-20.19)
Informativeness	-0.245***	-0.672***	-0.697***	-0.574***
	(-3.52)	(-5.90)	(-4.80)	(-4.62)
Informativeness × Q	-0.007	0.173***	0.174***	0.212***
	(-0.28)	(3.94)	(3.35)	(4.62)
Diversification	0.461	4.263***	5.104***	4.192***
	(0.59)	(3.57)	(3.41)	(4.19)
Diversification × Q	-0.022	-1.579**	-1.795**	-1.615***
	(-0.05)	(-2.32)	(-2.15)	(-3.31)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	18,830	18,830	13,647	13,647
Within R^2	0.195	0.293	0.334	0.271

Continued…

Specification (13) Bonacich+ Centrality (β = 0.03)				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Bonacich+)	0.127	0.593***	0.804***	0.722***
	(1.42)	(3.83)	(4.41)	(4.89)
Log(Bonacich+) × Q	**-0.088*** **	**-0.109** **	**-0.180*** **	**-0.093** **
	(-2.98)	**(-2.17)**	**(-3.23)**	**(-2.00)**
Log(Bonacich+) × CF	0.400	0.539	0.691	0.019
	(1.57)	(1.20)	(1.33)	(0.04)
Q	1.026***	1.680***	1.825***	0.875***
	(10.68)	(9.67)	(9.25)	(5.07)
CF	2.017***	3.836***	4.068***	2.357**
	(3.36)	(3.35)	(2.94)	(1.98)
Log(Assets)	-1.274***	-5.744***	-6.895***	-5.893***
	(-8.68)	(-20.77)	(-20.55)	(-20.25)
Informativeness	-0.257***	-0.676***	-0.710***	-0.570***
	(-3.75)	(-6.08)	(-5.05)	(-4.74)
Informativeness × Q	0.000	0.176***	0.180***	0.208***
	(0.01)	(4.16)	(3.64)	(4.80)
Diversification	0.547	4.311***	5.251***	4.197***
	(0.70)	(3.64)	(3.56)	(4.21)
Diversification × Q	-0.059	-1.585**	-1.823**	-1.588***
	(-0.14)	(-2.34)	(-2.20)	(-3.27)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	18,830	18,830	13,647	13,647
Within R^2	0.195	0.294	0.335	0.272

Continued…

Internet Appendix Table 7 (Continued)

Specification (14) Degree Centrality				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Degree)	0.114	0.624***	0.908***	0.778***
	(0.84)	(2.65)	(3.18)	(3.22)
Log(Degree) × Q	**-0.129****	**-0.116**	**-0.216****	**-0.072**
	(-2.44)	**(-1.38)**	**(-2.31)**	**(-0.90)**
Log(Degree) × CF	0.082	0.917	1.342	0.924
	(0.17)	(1.10)	(1.48)	(1.28)
Q	0.974***	1.559***	1.653***	0.732***
	(10.78)	(9.77)	(8.92)	(4.50)
CF	2.681***	4.142***	4.308***	1.655*
	(5.26)	(4.24)	(3.75)	(1.72)
Log(Assets)	-1.263***	-5.719***	-6.863***	-5.858***
	(-8.69)	(-20.64)	(-20.38)	(-20.17)
Informativeness	-0.245***	-0.680***	-0.707***	-0.585***
	(-3.50)	(-5.91)	(-4.81)	(-4.66)
Informativeness × Q	-0.007	0.176***	0.179***	0.217***
	(-0.27)	(3.95)	(3.37)	(4.64)
Diversification	0.470	4.309***	5.164***	4.248***
	(0.60)	(3.61)	(3.45)	(4.24)
Diversification × Q	-0.029	-1.601**	-1.826**	-1.643***
	(-0.07)	(-2.36)	(-2.19)	(-3.36)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	18,830	18,830	13,647	13,647
Within R^2	0.195	0.293	0.333	0.271

Continued…

Internet Appendix Table 7 (Continued)

Specification (15) Eigenvector Centrality				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Eigenvector)	2.507	9.381***	14.243***	11.493***
	(1.35)	(3.01)	(3.63)	(3.65)
Log(Eigenvector) × Q	**-1.692****	**-2.621*****	**-3.440*****	**-1.897*****
	(-2.10)	**(-3.31)**	**(-4.50)**	**(-2.63)**
Log(Eigenvector) × CF	10.956	28.972*	31.526**	19.339**
	(1.08)	(1.91)	(2.14)	(2.11)
Q	0.913***	1.569***	1.599***	0.764***
	(12.09)	(11.47)	(10.29)	(5.62)
CF	2.459***	4.019***	4.427***	1.789**
	(5.62)	(4.61)	(4.40)	(2.09)
Log(Assets)	-1.265***	-5.706***	-6.865***	-5.858***
	(-8.55)	(-20.56)	(-20.33)	(-20.11)
Informativeness	-0.243***	-0.654***	-0.684***	-0.558***
	(-3.60)	(-5.89)	(-4.83)	(-4.65)
Informativeness × Q	-0.003	0.166***	0.171***	0.203***
	(-0.14)	(3.91)	(3.44)	(4.69)
Diversification	0.495	4.204***	5.093***	4.089***
	(0.64)	(3.55)	(3.46)	(4.24)
Diversification × Q	-0.057	-1.579**	-1.830**	-1.601***
	(-0.14)	(-2.35)	(-2.23)	(-3.32)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	18,830	18,830	13,647	13,647
Within R^2	0.195	0.294	0.335	0.271

Continued…

Internet Appendix Table 7 (Continued)

Specification (16) Betwenness Centrality				
Dependent Variable	CAPEX	CAPEX + R&D	CAPEX + R&D (non-missing)	R&D (non-missing)
	(1)	(2)	(3)	(4)
Log(Betweenness + 1)	11.418	56.234**	70.560***	57.858**
	(0.83)	(2.23)	(2.79)	(2.30)
Log(Betweenness + 1) × Q	**-3.748**	**-13.634***	**-18.797*****	**-13.796*****
	(-0.45)	**(-1.95)**	**(-3.59)**	**(-2.88)**
Log(Betweenness + 1) × CF	-26.533	81.937	121.761	131.533
	(-0.20)	(0.41)	(0.69)	(1.54)
Q	0.833***	1.472***	1.460***	0.697***
	(11.92)	(11.37)	(9.96)	(5.56)
CF	2.757***	4.721***	5.193***	2.224***
	(7.53)	(6.17)	(5.84)	(2.92)
Log(Assets)	-1.264***	-5.685***	-6.814***	-5.815***
	(-8.57)	(-20.48)	(-20.23)	(-20.02)
Informativeness	-0.278***	-0.692***	-0.745***	-0.584***
	(-4.12)	(-6.25)	(-5.26)	(-4.90)
Informativeness × Q	0.011	0.179***	0.193***	0.211***
	(0.48)	(4.24)	(3.87)	(4.94)
Diversification	0.590	4.220***	5.132***	4.062***
	(0.76)	(3.51)	(3.41)	(4.19)
Diversification × Q	-0.088	-1.573**	-1.826**	-1.578***
	(-0.21)	(-2.33)	(-2.20)	(-3.27)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	18,830	18,830	13,647	13,647
Within R^2	0.194	0.293	0.333	0.270

Internet Appendix Table 8

Increase in Centrality and Firm-level Announcement Wealth Effects (Alternative Specifications)

This table investigates whether the stock market reacts more positively to the announcement of alliances if new alliances more largely increase the announcing firm's alliance network centrality. The dependent variables are cumulative abnormal returns (*CAR*). In Panel A, cumulative abnormal returns (*CAR*) are estimated over a 2-day (-1, 1) event-period using market-adjusted returns (CRSP value-weighted index). In Panel B, cumulative abnormal returns (*CAR*) are estimated over a 3-day (-1, 1) event-period using the market model (CRSP value-weighted index) in which parameters are estimated in the window (-239, 6) using at least 100 non-missing daily return observations. In Panel C, cumulative abnormal returns (*CAR*) are estimated over a 2-day (-1, 0) event-period using the same market model specification. *Log(Centrality)* (at t – 1) is a natural logarithm of the Bonacich centrality described in Section 2.2, measured at the previous year of alliance announcements. The main independent variable is *Log*(*ΔBonacich)* equal to the increase in Bonacich centrality of the announcing firm, calculated as the natural logarithm of one plus Bonacich centrality of alliance partner firm multiplied by 0.02 (Section 5.3). See Appendix 1 for the complete list of variable definitions. See Table 14 for the list of winsorized variables. Industry fixed effects are defined at the SIC 2-digit level. 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.

Panel A: 2-day (-1, 0) event window with market-adjusted returns				
Dependent Variable	2-day Market-Adjusted CAR			
	(1)	(2)	(3)	(4)
Log(Centrality) (at t – 1)	0.206***	0.256***	0.136**	0.181**
	(2.94)	(2.91)	(1.99)	(2.09)
Log(ΔBonacich)	**0.734*****	**0.801*****	**0.752*****	**0.803*****
	(4.94)	**(5.25)**	**(5.11)**	**(5.30)**
R&D Alliance	0.260	0.097	0.158	0.061
	(1.26)	(0.45)	(0.76)	(0.28)
Non-R&D Alliance	-0.370**	-0.342*	-0.346*	-0.338*
	(-1.98)	(-1.81)	(-1.86)	(-1.80)
Horizontal Alliance	0.203	0.033	0.048	0.003
	(1.13)	(0.17)	(0.27)	(0.02)
Log(Market Capital)	-0.565***	-0.621***	-0.321***	-0.363***
	(-9.46)	(-8.90)	(-5.17)	(-4.87)
ROA			-4.295***	-4.244***
			(-5.18)	(-4.70)
Cash Holding			1.499***	1.233**
			(2.83)	(2.12)
Leverage			0.573	0.435
			(1.04)	(0.71)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	6,782	6,782	6,782	6,782
Adjusted R^2	0.050	0.063	0.066	0.075

Continued…

Panel B: 3-day (-1, 1) event window with market model				
Dependent Variable	3-day Market Model CAR			
	(1)	(2)	(3)	(4)
Log(Centrality) (at t – 1)	0.168**	0.250**	0.109	0.171*
	(2.22)	(2.50)	(1.40)	(1.73)
Log(ΔBonacich)	**0.716*** **	**0.816*** **	**0.746*** **	**0.823*** **
	(4.45)	**(4.89)**	**(4.65)**	**(4.94)**
R&D Alliance	0.414*	0.237	0.341	0.210
	(1.86)	(1.01)	(1.54)	(0.91)
Non-R&D Alliance	-0.005	0.011	0.015	0.012
	(-0.03)	(0.05)	(0.07)	(0.06)
Horizontal Alliance	0.456**	0.377*	0.346*	0.358*
	(2.24)	(1.73)	(1.75)	(1.67)
Log(Market Capital)	-0.546***	-0.602***	-0.320***	-0.340***
	(-8.76)	(-8.30)	(-4.57)	(-4.16)
ROA			-4.329***	-4.455***
			(-5.11)	(-4.87)
Cash Holding			0.961*	0.902
			(1.80)	(1.52)
Leverage			0.423	0.419
			(0.73)	(0.64)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	6,782	6,782	6,782	6,782
Adjusted R^2	0.038	0.049	0.049	0.059

Continued…

Internet Appendix Table 8 (Continued)

Panel C: 2-day (-1, 0) event window with market model				
Dependent Variable	2-day Market Model CAR			
	(1)	(2)	(3)	(4)
Log(Centrality) (at t – 1)	0.182***	0.232***	0.114*	0.151*
	(2.73)	(2.71)	(1.73)	(1.80)
Log(ΔBonacich)	**0.757*****	**0.817*****	**0.781*****	**0.823*****
	(5.23)	**(5.51)**	**(5.44)**	**(5.59)**
R&D Alliance	0.298	0.151	0.208	0.122
	(1.52)	(0.74)	(1.06)	(0.60)
Non-R&D Alliance	-0.276	-0.248	-0.254	-0.245
	(-1.55)	(-1.38)	(-1.43)	(-1.37)
Horizontal Alliance	0.267	0.134	0.132	0.111
	(1.52)	(0.72)	(0.77)	(0.60)
Log(Market Capital)	-0.544***	-0.592***	-0.301***	-0.325***
	(-9.20)	(-8.64)	(-4.89)	(-4.46)
ROA			-4.463***	-4.532***
			(-5.54)	(-5.19)
Cash Holding			1.186**	0.941*
			(2.32)	(1.67)
Leverage			0.366	0.246
			(0.69)	(0.42)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	6,782	6,782	6,782	6,782
Adjusted R^2	0.049	0.060	0.065	0.074

Internet Appendix Table 9

Synergy: Combined Centrality and Combined Announcement Wealth Effects (Alternative Specifications)

This table investigates whether the stock market reacts more positively to the announcement of alliances involving firms with a higher alliance network centrality. In Panel A, cumulative abnormal returns (*CAR*) are estimated over a 2-day (-1, 1) event-period using market-adjusted returns (CRSP value-weighted index). In Panel B, cumulative abnormal returns (*CAR*) are estimated over a 3-day (-1, 1) event-period using the market model (CRSP value-weighted index) in which parameters are estimated in the window (-239, 6) using at least 100 non-missing daily return observations. In Panel C, cumulative abnormal returns (*CAR*) are estimated over a 2-day (-1, 0) event-period using the same market model specification. The dependent variable in odd-numbered columns is *Combined CAR* that is a value-weighted *CAR* of the portfolio of two firms, where the weight is determined by each firm's market capital measured 50 trading days before the announcement. The dependent variable in even-numbered columns is *Combined Dollar Gain* that is the sum of firms' dollar wealth gain: *CAR* multiplied by market capital at the beginning of the event period. *Combined CAR* is measured in percentage points, and *Combined Dollar Gain* is measured in million dollars. *Both Central* is an indicator variable that equals 1 if both firms' centrality values are above the median of centrality distribution within the event study sample, and 0 otherwise. *One Central* is an indicator variable that equals 1 if only one firm's centrality value is above the median of centrality distribution within the event study sample, and 0 otherwise. *Combined Centrality* is the sum of two firms' Bonacich centrality measured in the previous year of announcement. See Appendix 1 for the complete list of variable definitions. See Table 14 for the list of winsorized variables. 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.

Panel A: 2-day (-1, 0) event window with market-adjusted returns				
Dependent Variable	Combined CAR	Combined Dollar Gain	Combined CAR	Combined Dollar Gain
	(1)	(2)	(3)	(4)
Both Central	**0.554*****	**458.810*****		
	(2.95)	**(2.99)**		
One Central	0.004	-113.490		
	(0.02)	(-1.07)		
Combined Centrality			**0.002*****	**0.903**
			(3.25)	**(1.27)**
R&D Alliance	0.095	-67.632	0.069	-91.543
	(0.58)	(-0.43)	(0.42)	(-0.58)
Non-R&D Alliance	-0.039	-23.820	-0.052	-33.977
	(-0.24)	(-0.14)	(-0.32)	(-0.20)
Horizontal Alliance	-0.023	-12.468	-0.021	-12.663
	(-0.17)	(-0.11)	(-0.15)	(-0.11)
Combined Market Capital ($ billion)	-0.001	1.572	-0.001	1.539
	(-0.99)	(1.17)	(-1.57)	(1.08)
Year FE	Yes	Yes	Yes	Yes
Observations	3,391	3,391	3,391	3,391
R^2	0.009	0.018	0.007	0.013

Continued…

Internet Appendix Table 9 (Continued)

Panel B: 3-day (-1, 1) event window with market model				
Dependent Variable	Combined CAR	Combined Dollar Gain	Combined CAR	Combined Dollar Gain
	(5)	(6)	(7)	(8)
Both Central	**0.627*** **	**475.864** **		
	(2.82)	**(2.53)**		
One Central	0.173	98.623		
	(0.88)	(0.77)		
Combined Centrality			**0.001** **	**0.138**
			(1.97)	**(0.16)**
R&D Alliance	0.085	-82.323	0.067	-92.422
	(0.44)	(-0.44)	(0.34)	(-0.49)
Non-R&D Alliance	0.207	229.669	0.189	214.386
	(1.05)	(1.14)	(0.96)	(1.06)
Horizontal Alliance	0.141	148.019	0.140	143.175
	(0.84)	(1.07)	(0.84)	(1.03)
Combined Market Capital ($ billion)	-0.002**	-2.889*	-0.002**	-2.307
	(-2.21)	(-1.71)	(-2.08)	(-1.30)
Year FE	Yes	Yes	Yes	Yes
Observations	3,391	3,391	3,391	3,391
R^2	0.009	0.013	0.007	0.010

Panel C: 2-day (-1, 0) event window with market model				
Dependent Variable	Combined CAR	Combined Dollar Gain	Combined CAR	Combined Dollar Gain
	(5)	(6)	(7)	(8)
Both Central	**0.602*** **	**415.994*** **		
	(3.34)	**(2.80)**		
One Central	0.115	-72.674		
	(0.72)	(-0.70)		
Combined Centrality			**0.002*** **	**0.809**
			(3.17)	**(1.15)**
R&D Alliance	0.111	-49.038	0.089	-69.276
	(0.70)	(-0.32)	(0.56)	(-0.45)
Non-R&D Alliance	0.068	16.310	0.052	6.665
	(0.43)	(0.10)	(0.33)	(0.04)
Horizontal Alliance	0.061	14.476	0.062	14.139
	(0.45)	(0.13)	(0.45)	(0.12)
Combined Market Capital ($ billion)	-0.001*	0.989	-0.001**	0.978
	(-1.65)	(0.74)	(-1.98)	(0.69)
Year FE	Yes	Yes	Yes	Yes
Observations	3,391	3,391	3,391	3,391
R^2	0.009	0.011	0.007	0.008