The Impact of Partnership Network on Corporate Policy

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ABSTRACT

Using a large sample of U.S. firms engaging in corporate partnerships, this paper examines the impact of partnership connections on corporate leverage and investment decisions. Well-connected firms are centrally located in partnership networks and, therefore, are exposed to greater information flows through the networks. The informational advantages of central firms allow them to maintain unused debt capacity to opportunistically exploit new investment opportunities, and to rely less on other information for making investment decisions. Consistent with these hypotheses, I find that central firms use less debt and exhibit lower investment-to-price sensitivity. Subsample analyses using partnership types and financial constraints further support the premise that these results are driven by information flows through partnership connections. To establish causal interpretations, I exploit state-level corporate income reporting rules as a source of exogenous variations in the cost of partnership formations. Overall, this paper highlights the consequence of partnerships on corporate decisions, and thus provides a new facet of the interaction between product markets and corporate decisions.

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1. Introduction

Firms often collaborate with other firms, universities, and government institutions in a variety of sectors (Schilling 2015). Corporate partnerships such as joint ventures and strategic alliances emerge as organizational structures for collaborations that promote knowledge transfer and relationship-specific investments between partners.[1,2] In the theory of the firm, partnerships take an intermediate point on the market-hierarchy continuum (Williamson 1975) that provide tighter connections than simple arm's length market transactions (Johnson and Houston 2000) without sacrificing organizational flexibility (Chan, Kensinger, Keown, and Martin 1997). Previous research suggests that partnerships enhance firm value and performance[3], but provides little evidence on the consequence of partnership connections on specific corporate policies. In this paper, I investigate how partnership connections affect corporate financial and investment decisions.

To gauge the influence of partnership connections on corporate policies, I consider a network where firms are connected through partnerships (including joint ventures, licensing agreements, marketing agreements, manufacturing agreements, research and development agreements, and other forms of strategic alliances). In the partnership network, some firms are better connected than other firms. Since partnerships are specialized in sharing information, well-connected firms should be exposed to greater information flows and possess informational advantages. If these advantages help firms detect better or new investment opportunities, well-connected firms are expected to maintain unused debt capacity to respond to emerging

[1] Jensen and Meckling (1992) point out that a network organization such as partnerships may effectively reduce the cost of transferring specific knowledge among agents. Gomes-Casseres, Hagedoorn and Jaffe (2006) show that strategic alliances promote knowledge flows between partners.

[2] Johnson and Houston (2000) suggest that joint ventures can be more efficient in making relationship-specific investments than simple customer-supplier contracts. In the similar vein, Fee, Hadlock and Thomas (2006) and Kale and Shahrur (2007) use joint ventures and strategic alliances as a proxy for the degree of relationship-specific investments.

[3] For example, positive stock market reactions are observed for the announcement of joint ventures (McConnell and Nantell 1985; Johnson and Houston 2000) and strategic alliances (Chan, Kensinger, Keown, and Martin 1997). König, Liu and Zenou (2014) find that R&D partnerships increase Tobin's Q. Li, Qiu and Wang (2016) and Schilling (2015) provide evidence that alliances improve innovation performance.

investment opportunities in a timely manner (DeAngelo and DeAngelo 2007; Denis 2011). Moreover, the investment policy of these firms might be less sensitive to other sources of information, such as the firms' stock price (Chen, Goldstein, and Jiang 2007).

To empirically test these implications, I perform a network analysis on a large sample of U.S. firms engaging in corporate partnerships between 1994 and 2013. Network analysis is an effective framework to analyze information flows between *both* directly and indirectly connected firms (Jackson 2008). It is worth noting that taking account of "indirect" connections implies that partnership networks convey not only partnership-specific knowledge but also more general information such as industry or macroeconomic conditions, which extends the scope of the analysis from a single partnership to a global network-level. In a network of partnerships, the position of firms determines the degree of information flows to which firms are exposed. Network analysis captures this position in a concept "centrality" indicating how firms are centrally located in the network.[4] In sum, I begin with building a time-series of partnership networks and estimates the centrality of firms in the networks. Then I examine the effect of centrality in partnership networks on corporate leverage and investment policies.

The existing literature on network analysis provides several measures of centrality. In this paper, I use the Bonacich measure of centrality (Bonacich 1987). The Bonacich centrality is a popular measure of the influence of members in the networks, capturing the degree of information flows through both direct and indirect connections. The Bonacich centrality is conceptually similar to the eigenvector centrality popular in the network applications in finance research (Ahern and Harford 2014). However, the Bonacich centrality provides measurement flexibility to help this paper take account for substantial time-series variations in the partnership networks (as illustrated in Figure 1).[5] For instance, parametrizations allowed in the Bonacich

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[4] The idea of using network analysis has been popular in economics, and recently in finance research as well. For example, Anjos and Fracassi (2015) use industry-level input-output networks to proxy for the information structure embedded in the economy. They show that conglomerate firms benefit from the firms' excess centrality, a measure of information advantages compared to stand-alone firms.

[5] Section 2.3 discusses more details on the choice of centrality measures. Appendix 2 shows that my findings are robust to the choice of centrality measures.

centrality can avoid the overestimation of centrality in small and sparse networks.[6] It should be emphasized that this measurement flexibility facilitates a meaningful comparison of centrality across networks in different time periods.[7]

This paper first illustrates the trend of partnerships during the 1990s and 2000s. There was a dramatic surge in partnership activities during the early 1990s. Partnerships were at their peak in 1999 and 2000 but experienced a downturn afterwards. Since partnership networks consist of existing partnerships at certain moments, partnership networks accordingly expanded during the 1990s but reduced in the 2000s. This trend confirms the finding of Schilling (2015) that a major technology shock stimulated a surge in partnership activities during the 1990s as a response to increased uncertainty in economic environment. I further document that Initial Public Offering (IPO) activities are largely correlated with partnership trends, implying that young and growing firms are important in partnership formations. More interestingly, partnership networks consistently become coarser during the sample period. For example, Figure 1 shows that the size of partnership networks (measured by the number of participants in the networks) is about the same in 1994 and 2010, but the latter is apparently less clustered with sparser connections.

My first empirical tests examine the effect of centrality in partnership networks on firm leverage. A key rationale is that well-connected firms may use less debt to pursue financial flexibility. Financial flexibility implies retaining financial slack to pursue new projects when they emerge (DeAngelo and DeAngelo 2007; Denis 2011), which turns out to be one of the most important determinants of capital structure according to CFOs (Graham and Harvey 2001). Since central firms are well-connected and exposed to greater information flows through the networks, these firms have higher incentives to maintain unused debt capacity to avoid investment distortions due to financing frictions (Myers and Majluf 1984). Further, financial flexibility of central firms can encourage their partners to make relationship-specific investments, because partnership participants are expected to have strong commitments that essentially depend on the

[6] It is clear that any parametrization comes with the concern about the arbitrariness of parameter choices. Appendix 2 reports that my findings are robust to the choice of parameters.
[7] This time-series comparability is particularly important in estimations with firm fixed-effects.

financial stability of participants (Titman 1984). Consistent with this hypothesis, I find that more central firms use less debt. For example, the book (market) leverage of firms at the 75th percentile of the centrality distribution is 110 (64) basis points higher than firms at the 25th percentile. This result still holds when I control for the initial leverage of firms to capture permanent components of firm leverage (Lemmon, Roberts, and Zender 2008).

I further look at the effect of centrality in partnership networks on investment decisions. Specifically, I examine whether the investment policy of central firms is less sensitive to the firms' stock price, which has been documented as an important determinant of investment decisions. Chen, Goldstein and Jiang (2007) argue that managers may acquire some private information from the firm's stock price, thereby making corporate investments sensitive to stock prices.[8] If partnership connections convey useful information for investment decisions, more central firms may rely less on the information contained in stock prices due to their informational advantages. Supporting this argument, central firms' capital expenditure (CAPEX) is less sensitive to Tobin's Q that proxies for the firms' stock prices. Since many firms engaging in partnerships intensely invest in intangible capital as well, I also investigate research and development expenditure (R&D) separately and together with CAPEX as alternative measure of investment. My finding still holds for these intangible capital expenditure. Finally, I test whether these information advantages are value-enhancing, and find that more central firms are indeed associated with higher Tobin's Q. These results suggest that partnership networks are conduits of value-enhancing information and central firms do benefit from their informational advantages.

Since I cannot directly observe information flows, it is still unclear whether the above results are driven by the variation in information flows through partnership connections. To bolster my arguments, I analyze the effect of centrality in two subsamples. First, I construct a subsample based on whether firms are participating in joint ventures and R&D agreements.

[8] Several recent studies further look at the effect of changing information environment on investment-to-price sensitivity. Foucault and Frésard (2012) show that firms' cross-listing increases their investment-to-price sensitivity as the cross-listing expands the trading venue for informed traders. More recently, Chen, Huang, Kusnadi and Wei (2014) and Edmans and Jayaraman (2016) document the effect of changes in insider trading activities on the investment-to-price sensitivity.

Previous research suggest that joint ventures provide tighter connections (Villalonga and McGahan 2005) and better promote knowledge transfers between partners (Stonitsch 2014). Also, partnerships engaged in R&D activities naturally face higher chance of failures, thereby expecting greater information sharing between partners. Thus, information advantages would be even more valuable for central firms participating in joint ventures or R&D agreements. Consistent with this argument, I find that the effect of centrality on leverage and investment-to-price sensitivity is stronger for these firms.

My second subsample tests the role of financial constraints on the effect of centrality. Myers and Majluf (1984) show that financially constrained firms may skip some positive NPV projects due to their funding inability. In this case, central firms will bear higher opportunity costs because of their better ability to detect valuable investment opportunities. Hence, the effect of centrality on leverage might be stronger for financially *constrained* firms where the value of maintaining unused debt capacity would be greater. On the other hand, the effect of centrality on investment-to-price sensitivity might be stronger for financially *unconstrained* firms, since financially constrained firms are less likely to be able to exploit investment opportunities in a timely manner. My empirical tests also support these arguments, providing evidence that my empirical results are likely to be driven by information flows through partnership networks.

It should be pointed out that partnership formation is the result of corporate decisions and, thus, likely to be endogenously determined with other corporate policies. For example, previous research suggests that firm leverage and cash holdings might be determinants of partnership activities (Bodnaruk, Massa, and Simonov 2013; Li, Qiu, and Wang 2016). To pin down the direction of causality between partnership networks and corporate policies, I exploit state-level corporate income reporting rules as a source of exogenous variations in the cost of partnership formations, following Bodnaruk, Massa and Simonov (2013). Combined reporting treats the parent firm and its subsidiaries as a single entity for state income tax purposes (Mazerov 2009) and, therefore, restricts the firms' usage of internal capital markets (e.g. income transfer to tax-haven subsidiaries) to minimize their tax burden. If strategic alliances are alternatives to internal capital markets in conducting new projects (Robinson 2008), combined reporting reduces the opportunity cost of forming partnerships. I construct the industry-level index of combined reporting requirements, representing the *peer* firms' cost of partnership formations.[9] This peer index can affect the firm's incentive to engage in partnerships because firms tend to initiate connections with similar firms, which results in clustering in partnership networks (Schilling 2015). Moreover, it is hard to believe that peer firms' combined reporting index, based on the *geographic* locations of their subsidiaries, will have a *direct* influence on the firm's policies. My empirical results generally hold in the instrument variable estimations, though some endogeneity concern may still remain under the absence of useful natural experiments.

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

This paper highlights corporate partnerships as a new facet of the interaction between corporate policies and product market activities. Originating from the seminal work of Titman (1984), a vast literature provides evidence that customers and suppliers have profound impacts on corporate policies, including capital structure (Titman and Wessels 1988; Kale and Shahrur 2007; Banerjee, Dasgupta, and Kim 2008; Hennessy and Livdan 2009; Chu 2012), payout policy (Wang 2012), takeover defenses (Johnson, Karpoff, and Yi 2015), and investment decisions (Chu, Tian, and Wang 2015). The literature also documents that industry characteristics and product

[9] A firm-level index of combined reporting has been used as an instrument for partnership formations (Bodnaruk, Massa, and Simonov 2013; Li, Qiu, and Wang 2016). However, it is unlikely that this variable satisfies the exclusion condition of instrument variables, since combined reporting is likely to have direct effects on corporate policies and valuations via altering tax advantages and taxable income.

market competitions are important determinants of capital structure (Maksimovic and Zechner 1991; MacKay and Phillips 2005) and payout policy (Hoberg, Phillips, and Prabhala 2014). In contrast to supply chains and industry structures, partnerships have received little attention in the literature as a determinant of corporate policies. My research fills this gap. Also, more broadly, this paper adds to the literature on how organization structures and information environment can affect corporate financial and investment decisions.

Finally, this paper adds to an emerging literature on the application of network analysis in financial economics. Recently, network analysis is intensively used to model industry-level input-output structures (Ahern 2013; Ahern and Harford 2014; Anjos and Fracassi 2015), firm-level input-output structures (Gao 2015), and product similarities between firms (Hoberg and Phillips 2015). Although partnership networks have been studied in the economics and management literature (Hagedoorn 2002; Rosenkopf and Schilling 2007; Schilling and Phelps 2007; König, Liu, and Zenou 2014; Schilling 2015), this paper is the first study that builds partnership networks to study their consequences for corporate policy decisions. In addition, this paper provides a more comprehensive picture of partnership networks including a variety of partnership types and activities, which extends the previous literature on partnership networks concentrate on R&D collaborations.

The remainder of this paper proceeds as follows. Section 2 describes data and variables. Section 3 presents the empirical results. Section 4 concludes the paper.

2. Data and Variables

2.1. Overview of partnership trends

I obtain partnership data involving U.S. firms from Thomson Reuters SDC Platinum Joint Venture and Strategic Alliances database (SDC). SDC collects data from a wide range of industries, beyond manufacturing and biotechnological sectors where other datasets such as MERIT-CATI are also popular in the literature (Schilling 2009).[10] SDC provides by far the most comprehensive resource of a variety of partnership activities, including joint ventures, research and development agreements, licensing agreements, manufacturing or marketing agreements, and other forms of strategic alliances. These partnership activities are classified by SDC and not mutually exclusive. Since any partnership activities possess the nature of information flows and relationship-specific investments, I exploit all types of partnerships reported in SDC. Accordingly, this paper presents an extended picture of partnership networks broader than R&D partnership networks (Schilling and Phelps 2007; König, Liu, and Zenou 2014; Schilling 2015)

A partnership network consists of partnership connections originating from partnership deals. Partnership deals should meet the following screening criteria. First, a deal must be announced between 1990 and 2013, as SDC started a systematic data collection only in 1990. Second, a deal should not be classified as "rumored" or "intended" since these deals lack public announcements that establish actual connections. It is worth noting that this paper contains partnerships formed between three or more firms, broadening the previous literature that mostly focuses on bilateral partnerships. In sum, my partnership networks are built on 123,492 partnership deals between 99,623 unique participants.

Panel A of Table 1 summarizes the time-series trend of partnership activities between 1990 and 2013. The number of deals dramatically surged during the 1990s and peaked in 1999 and 2000, followed by a downturn during the 2000s. The effect of the financial crisis in the late 2000s is remarkable. The total number of announced deals between 2009 and 2011 is even less than the number in 2008. This trend of partnership activities is consistent with other recent alliance studies using SDC (Schilling 2015) or MERIT-CATI database (König, Liu, and Zenou 2014). Schilling (2015) attributes this pattern to a major technology shock that may have unveiled innovation opportunities but also increased the uncertainty in economic environment. During the early 1990s, technology shocks stimulated a surge in partnership activities to jointly explore new product and

[10] Due to the lack of mandatory filing requirements, no alliance database is complete in the sense that any database only captures a part of alliance activities existing in the world. Nevertheless, Schilling (2009) shows that replications of previous research using different datasets produce qualitatively similar results and concludes that there is no systematic bias between datasets.

technology opportunities. Once the uncertainty resolved to some extent, partnership demands gradually declined during the 2000s and significantly dropped after the financial crisis in the late 2000s. As a related explanation, Panel A suggests that partnership demands are largely correlated with the number of Initial Public Offering (IPO) firms. For example, a sharp change in the number of U.S. IPOs coincides with another sharp change in the number of announced partnership deals (e.g. 2000-2001, 2007-2008).[11] The next columns present the ratio of the number of U.S. participants in partnership deals to the number of U.S. IPOs for three-year moving windows. It turns out that after controlling for the supply of IPO firms, partnership demands were actually higher in the late 1990s and the early 2000s when the economy was experiencing the dot-com boom. This is a new finding that links partnership and IPO activities, implying that young and growing firms are important players in partnerships.

Panel B of Table 1 reports the time-series trend of partnerships by partnership activities. The table shows both the number of deals and the proportion of each partnership activity. These activities are not mutually exclusive. A partnership deal often involves contractual agreements on multiple activities. Interestingly, the proportion of joint ventures dramatically surged in recent years after the financial crisis in the late 2000s. This is a new finding that adds to the previously documented decline in joint ventures during the 1990s (Hagedoorn 2002). It seems that recent economic environment increases the benefit of joint ventures offering tighter connections, and this benefit outweighs the cost of sacrificing organizational flexibility from looser alliances.

2.2. Construction of partnership networks

SDC rarely reports the date of termination for a given alliance, creating a severe data limitation on measuring the ongoing status of partnerships. For example, only 1,699 out of 123,492 deals in my sample report the date of termination. Since it is unlikely that a partnership exists only for the year of formation, an assumption for the duration of alliances has been proposed in the literature. Previous empirical studies usually assume either a three- (Schilling and Phelps 2007;

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

Schilling 2015) or five-year (Robinson and Stuart 2007b; König, Liu, and Zenou 2014) duration for each alliance. In addition, I search the contract length information reported in SDC. Most alliances involve an open-length contract without any specified length of partnerships, but a small fraction of alliances specify the length of partnerships. Total 4,444 out of 123,492 deals in my partnership networks report the alliance duration with a mean of 8.72 and the median of 5 years. Accordingly, I use the five-year duration as my base specification of partnership networks. I also check the robustness of results with three- and seven-year assumptions of alliance durations. These additional results are qualitatively similar and provided in the Internet Appendix.

Using a five-year alliance duration, a partnership network in a given year t includes partnership deals announced in the previous five years (from $t - 4$ to t). I take a snapshot of partnership network at the end of each calendar year. For example, the partnership network in 1998 includes partnership deals announced between 1994 and 1998. Because of this five-year data requirement, my sample period begins in 1994 which is the first calendar year when partnership data is available for the previous five years. As a result, I obtain a time-series of partnership networks from 1994 to 2013.

A network consists of nodes (participants) and edges (connections). Following the literature on partnership networks, I represent a partnership network as an unweighted and undirected adjacency matrix. More precisely, a network is a $n \times n$ matrix where n is the number of nodes in the network. Each element of the matrix is equal to 1 if two nodes are connected and 0 otherwise. In other words, all connections are unweighted. An undirected network matrix implies a symmetric relationship between nodes. While this symmetry is less realistic, it has an important advantage that all eigenvalues of the network matrix are real, which is crucial to compute centrality measures used in the network analysis (Ahern and Harford 2014).

Table 2 summarizes the characteristics of partnership networks between 1994 and 2013. First of all, Panel A shows that partnership networks follow the same time-series trend with the number of announced partnership deals presented in Panel A of Table 1, but with a lag of three to five years. For example, the size of network is at a peak in 2000-2003 while the number of announced deals is at a peak in 1997-2000. Similarly, a sharp decrease of partnership deals in

2008-2009 seems to affect the size of network in 2012-2013. The summary statistics of networks are generally similar to those reported in recent alliance studies (König, Liu, and Zenou 2014; Schilling 2015). Finally, it is worth noting that a substantial decline in the size of partnership networks in the late 2000s might be exaggerated due to an inherently hypothetical nature of the duration of partnerships. If the assumption in the partnership length creates a downward bias in the actual length of partnerships, the observed shrinking networks can be partially attributed to the censored partnerships.

Panel A suggests that partnership networks have been gradually decentralized during the sample period. The average number of direct connections per participant (i.e., the average degree) has generally decreased until recent years despite the substantial fluctuations in the size of networks. As a result, partnership networks have become less clustered. It is also observed that there has been a decrease in the average clustering coefficient that measures the extent that a node's neighbors are connected with each other. Figure 1 helps to visualize the decentralization. For example, despite the similar number of nodes in 1994 and 2010, the figure clearly indicates that nodes have become more scattered, and thus less clustered even in the center of networks.

2.3. Measure of network centrality

Network centrality is the main variable of interest in this paper that captures the position of participants in the partnership network. As discussed in the introductions, some firms are better connected than other firms in the network. For example, Figure 1 illustrates that IBM and Microsoft are connected with many other firms, and in fact located in the central part of the network. In other words, network centrality distinguishes well-connected "central" nodes from isolated, less-connected "peripheral" nodes in the network.

In this paper, I use the Bonacich measure of power and centrality (hereafter the "Bonacich centrality") (Bonacich 1987) to measure the influence and information structure embedded in the networks. The Bonacich centrality relies on the notion that a node's importance is determined by how important the node's neighbors. Specifically, the Bonacich centrality not only accounts for the quantity of direct connections but also considers the quality of connections in terms of the importance of indirect connections through neighbors. As a result, the Bonacich centrality is a popular measure of "influence" of a node in network analysis (Robinson and Stuart 2007b; König, Liu, and Zenou 2014)

It is worth discussing the benefit of using the Bonacich centrality in this paper rather than other centrality measures popular in the literature. There are four other popular centrality measures used in the economics and finance literature: degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality. First, the degree centrality captures the number of direct connections for a given node in the network. The degree centrality is unable to measure the effect of indirect connections existing on the network, and thus fits less to this paper that presumes that information flows occur along indirect connections as well as direct connections.

The betweenness centrality measures the degree at which a node is well located in terms of shortest paths. Specifically, a node's betweenness centrality is high when the node is located on the shortest paths between many other nodes. On the other hand, the closeness centrality measures the distance of a given node to any other node in the network. More precisely, the closeness centrality is inversely related to the average of the shortest paths from a given node to all other nodes in the network. Both centrality measures share the assumption that "flows" occur along the shortest paths between nodes. Yet, Borgatti (2005) points out that information flows are less likely to satisfy this assumption, since knowledge transfer can happen along any paths, not necessarily limited to the shortest path between two nodes. Thus, these centrality measures are less appropriate for this paper focusing on the information flows between participants in partnership networks.

Lastly, the eigenvector centrality is the one that is similar to the Bonacich centrality in terms of the idea and calculation. Like the Bonacich centrality, the eigenvector centrality captures the effect of indirect connections and is free from the assumption of flows along the shortest paths. However, the Bonacich centrality is preferred in this paper to account for substantial time-series variations in the size and density of partnership networks reported in Table 2. The Bonacich centrality allows some parametrization to control for heterogeneity in network characteristics, whereas this measurement flexibility is unavailable for the eigenvector centrality. Certainly, the benefit of parametrization comes at the cost of the concern about the arbitrariness of parameter choices. The eigenvector centrality can be a better measure of centrality when networks are stable across time, or even time-invariant. For example, Ahern and Harford (2014) use the eigenvector centrality to measure an industry's position in the industry network. The eigenvector centrality fits well to their research as they use a static industry network measured in 1997. On the other hand, this paper investigates considerably time-varying networks, and thus the measurement flexibility of the Bonacich centrality is desirable to exploit such time-series variations.[12]

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

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

where $\boldsymbol{G}$ is an $n \times n$ adjacency matrix, $\boldsymbol{I}$ is an $n \times n$ identity matrix, and $\mathbf{1}$ is an $n \times 1$ vector of ones. For a sufficiently small value of β, $\boldsymbol{C}$ is well defined. α is a scaling factor and β is a decay factor that discounts the effect of indirect connections. Details of the construction of the Bonacich centrality are provided in Appendix 2. While the choice of α and β can be arbitrary, some earlier works suggest a guideline to the choice of parameters. Following Robinson and Stuart (2007b), I set β equal to three-quarters of the reciprocal of the largest eigenvalue of $\boldsymbol{G}$. In addition, I choose α such that the minimum centrality always equals to unity, normalizing the size of networks.[13] The idea is that for any partnership networks, it might be reasonable to treat the least connected nodes equivalently, i.e., nodes connected with only one other node in the network. Further, any parametrization of the Bonacich centrality preserves the ordinal ranking of centrality within a network, to the extent that the measure is well-defined (β is sufficiently small).[14]

[12] For robustness check, I run all empirical tests using the degree and eigenvector centrality. Appendix 2 shows that the results are qualitatively similar.

[13] My selection of scaling parameter is different from Robinson and Stuart (2007b) that choose α such that $\boldsymbol{C}'\boldsymbol{C} = n$. This parametrization scales the measure of centrality upward for small networks. For example, the mean centrality in 2013 would be substantially larger than the mean centrality in 2000. Figure 1 shows that this number is less intuitive and inconsistent with the decentralization described in Section 3.1.

[14] For robustness check, I run all empirical tests using two other parameter values for β (one smaller and one larger than the original choice of β). Appendix 2 shows that the results are almost unchanged.

Panel B of Table 2 shows the summary statistics of the Bonacich centrality. First of all, the decreasing mean of centrality is consistent with the decentralization in partnership networks observed in Panel A. Interestingly, Panel B shows that the decentralization is likely attributed to nodes with centrality above median. While the median centrality decreases by half from 2.07 to 1.00 during the sample period, the 99th percentile of centrality decreases by 78% from 117.71 to 26.30. This result is further confirmed by the graphical illustration in Figure 1. For instance, even the most central group of nodes in 2013 are less clustered and less connected than those in earlier networks. Thus, I conclude that to some extent my normalized centrality measures effectively control for the difference in the size and density of networks.

Panel B also shows that the Bonacich centrality is highly right-skewed, which can distort the estimation results in linear specifications. Following Ahern (2013), I use a log-transformed value of the Bonacich centrality as the main variable of interest in my empirical tests. Specifically, I construct a variable *Centrality* defined by a natural logarithm of the Bonacich centrality. In the population of nodes (i.e. all 547,036 nodes in networks), *Centrality* has a mean of 0.84, a standard deviation of 1.07, and a skewness of 1.55.

2.4. Summary statistics

Due to the nature of regional heterogeneity and limited data for foreign corporations, I focus on the sample of U.S. firms to examine the impact of partnership networks on corporate policies. My procedure of sample selection generally follows a vast literature on corporate policy. Of all firms in the Compustat/CRSP merged database, I first exclude financial (SIC 6000–6999) and utility (SIC 4900–4999) firms to avoid the strong effect of regulations on these firms. Sample firms should have non-missing values for the following variables: Tobin's Q, tangibility, cash flow volatility, book leverage, market leverage, cash, capital expenditures (CAPEX), and the status of paying dividends (Dividend Payer). My final sample consists of 31,827 firm-year observations in partnership networks between 1994 and 2013. See the Appendix 1 for the complete list of variable definition.

As an illustration of key firms, Table 3 lists top 25 central U.S. firms in partnership networks for six different years between 1994 and 2013. I report rankings only for selected years to present distinct changes in key firms, since networks are overlapping in a short horizon by construction. First of all, Table 3 identifies several giant firms in partnership networks, such as IBM, Microsoft, HP, GE, GM, and AT&T. It is unsurprising that these firms consistently have been among the most central firms in partnership networks and they have been highly influential on other firms in the networks. Table 3 also includes several firms operating in media/entertainment sectors, such as News Corp, Time Warner, and Walt Disney. This result shows that partnership networks in this paper capture partnership activities between participants in a wide range of industries, which extends the previous literature that generally focuses on manufacturing sectors. Figure 1 visualizes the network for selected years with the indication of network positions of key firms reported in Table 3. The figure suggests that even the most central firms contribute to the decentralization observed during the sample period. For example, many key firms were densely located in 1994, but they became more scattered in 2010 despite the similar size of network.

Table 4 provides descriptive statistics for the variables used in my empirical tests. All variables except for indicator, log-transformed, or bounded variables are winsorized at the 1st and 99th percentiles to prevent the effect of extreme outliers on the estimation results. The sample mean of *Centrality* is 1.56, which is greater than the population mean of *Centrality* of 0.84. This sample mean roughly corresponds to the 75% percentile of the population distribution of *Centrality*. This result is unsurprising based on the fact that my sample firms are public firms that are likely to have more connections than small and young private firms. All other statistics in Panel A are generally similar to those reported in a recent literature such as Leary and Roberts (2014) and Hoberg, Phillips and Prabhala (2014).

Panel B presents the correlation coefficients table between *Centrality* and other key variables used in my empirical tests. *Centrality* is positively correlated with firm size and age, suggesting that mature firms are more likely to locate centrally in partnership networks. Also, the positive correlation between *Centrality* and Q or R&D indicates that growth, technologyintensive firms are more likely to be central firms in networks. It is also worth noting that *Centrality* is negatively correlated with book leverage, consistent with my hypotheses.

Finally, Panel C reports the correlation between partnership types and activities classified by SDC. For example, the correlation between joint ventures and licensing agreements measures the likelihood that firms participating in joint ventures are also participating in licensing agreements. It should be pointed out that these categories are not mutually exclusive and their sum can exceed 100%. Joint ventures and R&D agreements mainly draw our interest since they will serve as a basis of subsample analysis in the following sections. It turns out that joint ventures are mostly correlated with manufacturing agreements, while R&D agreements are mostly correlated with licensing agreements. Given that licensing agreements typically involve technological resources such as patents, the observed high correlation between R&D and licensing agreements are unsurprising. On top of that, the correlation between joint ventures and R&D agreements is about 0.06, suggesting that they will create fairly distinct subsamples, which will be desirable for the purpose of analysis.

3. Empirical Results

3.1. Main results

3.1.1. Centrality and leverage

In this section, I test whether more central firms maintain a lower leverage (*Hypothesis 1*). Following Frank and Goyal (2009) and Leary and Roberts (2014), I estimate the following equation,

$$Leverage_{i,t} = \alpha + \beta \times Centrality_{i,t-1} + \boldsymbol{\Gamma} \times \boldsymbol{X}_{i,t-1} + \epsilon_{i,t} \quad (2)$$

where $Leverage_{i,t}$ is the leverage of firm i in year t, $Centrality_{i,t-1}$ is a natural logarithm of the Bonacich centrality of firm i in year $t-1$, and $\boldsymbol{X}_{i,t-1}$ is a vector of control variables in year $t-1$. All independent variables are lagged by one year to prevent any contemporaneous effects of these variables on leverage.

The literature on capital structure has documented an extensive list of determinants of leverage, which makes researchers virtually impossible to control all of them. Thus, following Leary and Roberts (2014), I include a set of control variables that most commonly appeared and turned out to be powerful in the literature.[15] Specifically, I control size, age, Q, capital expenditure, tangibility, ROA, cash flow volatility, SG&A, R&D, and whether firms pay dividends or not. To rule out any time-specific effects on leverage, I also include calendar year fixed-effects. Since industry characteristics are important determinants of leverage (MacKay and Phillips 2005), I include industry fixed-effects in all specifications except for the panel regression with firm-fixed effects. I further control for the industry median leverage based on SIC four-digit industries, reflecting that peer firms' leverage is an important determinant of the firm's leverage Leary and Roberts (2014).

Still, some unobservable heterogeneity in firm characteristics may simultaneously affect both the network centrality and corporate policies. Using firm fixed-effects is a popular technique to alleviate this concern. However, it has some limitations in my empirical tests. First of all, the centrality measure is sticky by construction, as my partnership networks are built on partnerships that are rolled over five years. Moreover, the duration of alliances is inherently hypothetical due to the limitation of data, thereby creating considerable measurement problems. It is worth noting that exploiting cross-sectional variations in the centrality would suffer less from measurement errors, because it is less likely that the difference between hypothetical and actual durations is systematically biased in a cross-section of firms. However, exploiting time-series variations *within* a firm is more vulnerable to measurement errors because the difference between hypothetical and actual durations is likely to be correlated within a firm. Further, once established partnerships

[15] Parsons and Titman (2008) provide an extensive review of empirical research on capital structure. For a summary of more recent research, I refer readers to Graham and Leary (2011).

may have a long-lasting effect even after the end of actual durations, implying slow changes in a firm's actual position in partnership networks. Finally, because of slow changes in leverage within a firm, using firm fixed-effects in the leverage regression may produce statistically insignificant results even though actual relationships are significant (Kale and Shahrur 2007).

As an imperfect remedy, I include the initial leverage for each firm in the regressions. This control is motivated by Lemmon, Roberts and Zender (2008) that document a strong persistence in the leverage within a firm. More precisely, the initial leverage accounts for any firm-specific time-invariant factors affecting time-invariant firm-specific components of leverage. I mainly use the first non-missing value of leverage from Compustat to proxy the initial leverage. However, some old firms may largely evolve from their initial status, resulting in a huge change in their market positions and business operations. Therefore, for firms that appeared in Compustat before 1990 when my partnership data begins, I use the leverage in 1990 to proxy for the initial leverage.[16]

Table 5 reports the estimation results of leverage regressions. Columns (1) and (3) show the coefficient of *Centrality* on book and market leverage from OLS models. The coefficient is negative and statistically significant at the 1% level. The economic significance is non-negligible. According to the OLS estimates, a one standard deviation increase in *Centrality* decreases leverage by 70(market)–120(book) basis points. Moreover, this effect becomes stronger for the group of firms with a higher centrality. For example, compared to the leverage of firms at the 25th percentile of the centrality distribution, the leverage of firms at the 75th percentile is higher by 64–110 basis points (0.92 standard deviations increase). On the other hand, the leverage of firms at the 90th percentile is 103–176 basis points (1.47 standard deviations increase) higher than the leverage of firms with the median centrality. This result suggests that maintaining financial flexibility by choosing low leverage is more important for highly central firms in partnership networks. Overall, Table 5 confirms that the centrality in partnership networks has negative impacts on leverage,

[16] In an unreported result, I use the first non-missing value of leverage from Compustat to proxy for the initial leverage for all firms as in Lemmon, Roberts and Zender (2008). The statistical significance of the initial leverage becomes weaker since it may fail to capture substantial changes in firm status. Nevertheless, the results remain virtually unchanged.

and these results are less likely to be driven by omitted variables or unobservable heterogeneity in industry characteristics.

While having some limitation discussed above, the fixed-effects estimation is a correct treatment to produce consistent estimates under the presence of unobserved heterogeneity (Gormley and Matsa 2014). Thus, in addition to the standard OLS regressions, I also run panel regressions with firm fixed-effects. Columns (2) and (4) show that the coefficients are statistically insignificant, although they are still negative. This result is consistent with the above discussion of limitations of using firm fixed-effects in this paper.

The coefficients of control variables are generally consistent with the previous empirical research. Particularly, the strongly positive coefficient on the industry median leverage shows that peer firms' leverage is a strong determinant of leverage Leary and Roberts (2014). Also, the coefficient on the initial leverage shows a similar level of statistical significance to that of the industry median leverage. This result supports the finding of Lemmon, Roberts and Zender (2008) that permanent components of leverage play an important role in determining leverage during the life of a firm.

3.1.2. Centrality and investment-to-price sensitivity

This paper presumes that partnership networks can convey not only partnership-specific knowledge but also broader categories of information with regards to technology, product market, and economic conditions. In this section, I examine one channel by which information flows through partnership networks may affect corporate investment policies. Specifically, I test whether more central firms rely less on information contained in stock prices for making investment decisions, showing a lower investment-price sensitivity. Previous research suggests that firms learn from their stock price to the extent that stock prices contain private information unavailable to managers. For instance, Chen, Goldstein and Jiang (2007) document a higher investment-price sensitivity for firms when stock prices are more informative. In the same vein, I expect that more central firms will exhibit a lower investment-to-price sensitivity because their informational advantage reduces the need to learn from their stock price.

I estimate the following form of investment equation with the centrality measure and its interaction terms,

$$I_{i,t} = \alpha + \beta_1 \times Centrality_{i,t-1} + \beta_2 \times Q_{i,t-1} + \beta_3 \times Centrality_{i,t-1} \times Q_{i,t-1} + \boldsymbol{\Gamma} \times \boldsymbol{X}_{i,t-1} + \epsilon_{i,t} \quad (3)$$

where $I_{i,t}$ is the investment measure of firm i in year t, $Centrality_{i,t-1}$ is a natural logarithm of the Bonacich centrality of firm i in year $t-1$, $Q_{i,t-1}$ is a proxy for the stock price of firm i measured at year $t-1$, and $\boldsymbol{X}_{i,t-1}$ is a vector of control variables in year $t-1$. The coefficient of interest is β_3 that represents the investment-to-price sensitivity of firm i in year t. For the investment measure of investment, I use capital expenditure (CAPEX) as well as R&D and the sum of CAPEX and R&D to capture intangible capital investments. Control variables include the followings. I first control for cash flows (measured by ROA) and the interaction of *Centrality* with cash flows due to the well-known effect of cash flows on investments (Fazzari, Hubbard, and Petersen 1988). Also, previous literature suggests that Q might be a poor proxy for investment opportunities (Erickson and Whited 2012). Therefore, I include one-year sales growth as a non-price based proxy for investment opportunities, following Asker, Farre-Mensa and Ljungqvist (2015). I also control for the firm size (log of market value), and include calendar year and industry fixed-effects based on SIC 4-digit industries. Finally, the investment variable and the cash flow variable are scaled by the beginning value of total assets to maintain a consistency in the measurement timing with *Centrality* and Q.[17]

Table 6 reports the estimation results. Due to the firm-year observations with missing R&D, the number of observations is smaller when R&D is included in the investment measure. First of all, Columns (1), (3) and (5) estimate an OLS model with calendar year and industry fixed-effects. In all specifications, the coefficient on the interaction term of *Centrality* with Q is negative

[17] Following Chen, Goldstein and Jiang (2007), I use total assets instead of total capital (usually measured by net property, plant and equipment) to scale variables, because my sample consists of a number of non-manufacturing firms. Notice that I also include R&D as an alternative measure of investments that less depends on the size of physical assets.

and statistically significant. This finding supports *Hypothesis* 2 that central firms in partnership networks may have less need to learn from stock prices due to their informational advantages.

As a robustness check, I control for firm fixed-effects in Columns (2), (4) and (6) instead of industry fixed-effects. In other words, my tests only exploit the within-firm variations in *Centrality* and Q. The results are virtually unchanged in terms of the magnitude of coefficients as well as their statistical significance. Indeed, this result is consistent with the idea of Roberts and Whited (2012) pointing out the inefficiency of using firm fixed-effects in the estimation with first-differenced variables, for example investments.

3.2. Cross-sectional analyses

3.2.1. Partnership types

This section examines the variation in partnership types as an underlying factor that may affect the observed impact of partnerships on corporate decisions. Specifically, I focus on joint ventures and R&D agreements as they have been documented to require a higher degree of connections between partners (Villalonga and McGahan 2005). First of all, joint venture is a specific form of partnerships having several unique features in contrast to strategic alliances. Joint ventures are close to hierarchical organizations as they typically involve equity investments of parent firms and establish a separate entity. If joint ventures offer a tighter connection between partners, then the degree of knowledge and information flows should be greater within joint ventures than strategic alliances. Stonitsch (2014) shows that the increase in cross-citations for partners' patents is larger for joint ventures than strategic alliances, suggesting that knowledge flows are greater within joint ventures. In sum, joint ventures are expected to provide tighter relationships that promote information flows between partners and provide strong incentives to sustain partnerships. This argument predicts that the effect of centrality in partnership networks will be stronger for firms participating in joint ventures rather than those only participating in strategic alliances.

Similarly, firms participating in R&D agreements may have more incentives to preserve financial flexibility to ensure partners' relationship-specific investments. Powell (1990) argues that relational (implicit) contracting is a critical feature of partnerships. Contractual details in partnerships are largely incomplete, and this incompleteness becomes even more severe when firms engage in R&D activities that naturally face a high chance of project failures (Lerner and Malmendier 2010). Thus, I expect that the effect of centrality in partnership networks will be stronger for firms participating in R&D agreements.

I construct subsamples based on whether a firm-year observation is participating in at least one joint venture or one R&D agreement. For both joint ventures and R&D agreements, about 30% of firm-year observations participate in these types of partnership. Empirically, I estimate Equations (2) and (3) with all control variables in Tables 5 and 6 including calendar year and industry fixed-effects. Table 7 shows the estimation results. Columns (1) – (4) of Panel A show that the negative relation between the centrality and leverage is stronger for firms participating in joint ventures. Columns (5) – (10) show that the negative effect of centrality on investment-price sensitivity is also stronger form firms participating in joint ventures, while the statistical significance seems weaker when I use R&D as a sole investment measure.

Panel B shows the estimation results for R&D agreement and non-R&D agreement subsamples. The results are qualitatively similar to those in Panel A. Interestingly, the effect of centrality on investment-price sensitivity is strong for firms participating in R&D agreements only when R&D is included in the investment measure. This finding suggests that information that these firms receive from partners are likely to be more informational on R&D expenditures than capital expenditures. In sum, the effects of centrality on corporate decisions are stronger for firms participating in joint ventures and R&D agreements that require higher commitments.

3.2.2. Financial constraints

Finance literature has built an extensive literature on the relation between firms' financial constraints and firm policy. For example, financial constraints often measure the unused debt capacity as it is closely related with the future borrowing. Moreover, financially constrained firms may skip some positive NPV projects due to their inability to fund the projects without external financing (Myers and Majluf 1984). This paper is built on the premise that partnership networks are conduits of information and more central firms have higher incentives to build financial flexibility to respond to value-enhancing information and investment opportunities. Therefore, the effect of centrality on leverage should be stronger for financially *constrained* firms, because the value of maintaining unused debt capacity is greater for these firms. On the other hand, the effect of centrality on investment-price sensitivity would be stronger for financially *unconstrained* firms, since financially constrained firms are likely unable to exploit investment opportunities in a timely manner.

To test these arguments, I estimate Equations (2) and (3) for subsamples based on firms' financial constraints. Since the finance literature has no unanimous agreement with a proper measure of financial constraints, I use three popular indices of financial constraints: WW Index (Whited and Wu 2006), KZ Index (Kaplan and Zingales 1997; Lamont, Polk, and Saá-Requejo 2001), and SA Index (Hadlock and Pierce 2010). A detail of these indices is described in Appendix 1. Firms are included in the financially constrained subsample if their index values are greater than or equal to the 67th percentile of the index distribution of my 31,827 sample firms. On the other hand, firms are classified as financially unconstrained if their index values are smaller than or equal to the 33rd percentile of the index distribution. As in the previous section, I use all control variables from Tables 5 and 6 including calendar year and industry fixed-effects.

Table 8 presents the results of subsample analysis based on financial constraints. Panels A and B show that the effect of centrality on leverage is stronger for the financially constrained subsample. Across all financial constraints measures, the coefficient on *Centrality* is greater in magnitudes and more statistically significant for financially constrained firms. It is worth noting that the result still holds when I use SA Index which is free of using leverage as a part of measures. On the other hand, Panels C – E show that the effect of centrality on investment-price sensitivity is stronger for the financially unconstrained firms. Generally, the coefficient on the interaction term of *Centrality* and Q is greater in magnitudes and statistically significant for financially unconstrained firms, while the results are weaker or reversed in R&D as the investment measure or KZ Index as the measure of financial constraints.

3.3. Endogeneity issues

The research objective of this paper is to study the impact of centrality in partnership networks on corporate financial and investment policies. If partnership networks are exogenous to corporate policies, a standard OLS estimation will produce unbiased and consistent estimates. However, forming partnerships is a part of corporate decisions and is likely to be endogenously determined with other corporate policies. For example, previous research suggests that leverage and cash holdings might be determinants of alliance activities (Bodnaruk, Massa, and Simonov 2013; Li, Qiu, and Wang 2016). Specifically, these papers document that the number of strategic alliances and joint ventures are negatively affected by leverage but positively affected by cash holdings. Hence, it is imperative to establish the direction of causalities from the centrality in partnership networks to corporate policies.

I exploit state-level corporate income reporting rules as a source of exogenous variations in the cost of partnership formations, helping to pin down the direction of causalities. A number of firms operate subsidiaries in multiple states, and each state have different requirements for reporting income of these subsidiaries. More than one third of U.S. states adopt combined reporting rules that treat the parent and subsidiaries of corporations as a single entity for state income tax purposes (Mazerov 2009).[18] On the other hand, separate reporting rules requires each subsidiary (including the parent) to report income to the state in which it operates. Bodnaruk, Massa and Simonov (2013) argue that combined reporting makes it less costly to engage in alliances. This is because combined reporting restricts the firms' ability to exploit internal capital markets for tax-planning purpose, reducing the benefit of internal capital markets. According to the view of strategic alliances as a commitment technology to new projects which is an alternative to internal capital markets (Robinson 2008), combined reporting reduces the opportunity cost of

[18] Appendix 3 lists the current status of states with combined reporting requirements.

forming alliances. Thus, it is expected that firms with more operations located in states under combined reporting requirements are more likely to form partnerships.

The Appendix D of Bodnaruk, Massa and Simonov (2013) provides detailed information on the construction of the firm-level combined reporting index that requires data on the locations of corporate subsidiaries.[19] Li, Qiu and Wang (2016) also use this firm-level index of combined reporting to establish the causality between alliance activities and innovation outcomes. I have the same data and follow their methods. Data on subsidiaries are available for 1998, 2000, 2002, and 2004. To avoid any potential look-ahead bias, I use the 1998 data for firm-year observations in 1997-1998, the 2000 data for observations in 1999-2000, the 2002 data for observations in 2001-2002, and the 2004 data for observations in 2003-2004.

However, using this firm-level index as an instrument likely fails to satisfy the exclusion condition. Combined reporting alters tax advantages and the amount of taxable income, and thus is likely to directly affect corporate policies. To avoid this problem, I construct the industry-level index of combined reporting requirements, representing the peer firms' cost of partnership formations. Previous research shows that firms are more likely to initiate partnerships with similar firms and tend to form clusters in partnership networks (Schilling 2015). Therefore, the peer firms' cost of engaging in partnerships can affect the firm's partnership formations, and thus will affect the centrality in partnership networks. More importantly, it would be a less concern that the peer firms' combined reporting requirements *directly* affect the firm's leverage and investment policies. I aggregate the firm-level index of combined reporting at the four-digit SIC industry-level and construct the peer index by excluding the firm's combined reporting index. The limitation in data availability reduces my sample size to 11,308 firm-year observations.

I estimate a two-stage least squares (2SLS) regression using this industry-level index of combined reporting, *Combined Reporting*, as an instrument for a firm's centrality in partnership networks. However, Gormley and Matsa (2014) point out that using industry average variables is unable to control for unobservable heterogeneity in industry characteristics. Thus, I also include

[19] I thank Andriy Bodnaruk for providing data on corporate subsidiaries.

industry fixed-effects based on two-digit SIC industry classifications in my 2SLS estimations. I use two-digit SIC industries because my instrument variables are constructed at four-digit SIC industries, which exhibits little variations within three-digit SIC industries. For leverage, I further control for peer firms' median leverage at two-digit SIC industries, since Leary and Roberts (2014) document a strong influence of peer firms' leverage on the firm's capital structure choice.

Table 9 reports the estimation results for leverage and investment-price sensitivity. Columns (1) and (2) test the effect of *Centrality* on leverage. The first-stage result shown in the bottom of columns confirms that *Combined Reporting* is a strong predictor of *Centrality*. Thus, the instrument meets the relevance condition. The Kleibergen-Paap rk LM Statistic also rejects that the excluded instruments are irrelevant with the endogenous regressors. Further, the endogeneity test (Wooldridge 1995) rejects that the endogenous regressors are in fact exogenous given the choice of instruments. Proceeding to the second-stage, the coefficient on *Centrality* is negative and statistically significant at the 1-5% level. In a similar way, Columns (3) – (5) test the effect of *Centrality* on investment-price sensitivity. The coefficient on the interaction term of *Centrality* with Q is still negative for CAPEX as a measure of investments. However, the coefficient loses its statistical significance but turns to positive for R&D and the sum of CAPEX and R&D as the investment measure. This insignificant result may stem from the problem of weak instruments, suggested by the Kleibergen-Paap rK LM Statistics that cannot reject that instruments are irrelevant with endogenous regressors. In sum, instrument variable estimations partially alleviate our identification concerns, though some issues may still remain in the absence of useful natural experiments.

3.4. Valuation effects

While my previous finding suggests that partnership networks may convey useful information for investment decisions, it is still an empirical question whether the information is value-enhancing. For example, some information might be redundant, or even value-destructive if it leads to managers' overinvestments. Hence, this section examines the value implication of partnership network centrality. If partnership networks are conduits of value-enhancing information, I should observe a positive association between *Centrality* and Tobin's Q.

Specifically, I estimate the following valuation equation,

$$Q_{i,t} = \alpha + \beta \times Centrality_{i,t} + \boldsymbol{\Gamma} \times \boldsymbol{X}_{i,t} + \epsilon_{i,t} + \epsilon_{i,t} \quad (4)$$

where $Q_{i,t}$ is Tobin's Q of firm i in year t, $Centrality_{i,t}$ is a natural logarithm of the Bonacich centrality of firm i in year t, and $\boldsymbol{X}_{i,t}$ is a vector of control variables in year t. Following the previous literature such as Bebchuk, Cohen and Ferrell (2009), I control for firm size and age, ROA, R&D, Book Leverage, CAPEX, and an indicator variable of whether a firm is incorporated in the State of Delaware. I also include calendar year and industry fixed-effects.

Table 10 presents the estimation results. Column (1) estimates an OLS model with calendar year and industry fixed-effects. The coefficient on *Centrality* is positive and statistically significant at 1% level. To ease the concern of endogenously determined network position and valuation, Column (2) estimates a two-stage least squares (2SLS) regression using *Combined Reporting* as an instrument for a firm's centrality in partnership networks. Still the coefficient on *Centrality* is negative and statistically significant at the 5% level. Thus, I conclude that stock market seems to positively evaluate the centrality in partnership networks, consistent with the previously documented positive announcement effects (McConnell and Nantell 1985; Chan, Kensinger, Keown, and Martin 1997; Johnson and Houston 2000; Stonitsch 2014).

4. Conclusion

This paper performs a network analysis for a large sample of corporate partnerships to study the impact of partnerships on corporate financial and investment policies. Firms located in the central part of networks are more likely to be exposed to greater information flows and are more influential to other firms in networks. I hypothesize that financial flexibility would be a desirable goal for these firms, since more central firms have more incentives to timely exploit useful information flowing through the network. Also, these firms have higher needs to provide incentives for their partners to make relationship-specific investments, which essentially depends on the firms' financial stability. Consistent with my hypotheses, I find that more central firms use less debt. More central firms in partnership networks also exhibit lower sensitivity of investment to stock prices and higher Tobin's Q, suggesting that partnership networks convey value-enhancing information for investment decisions. I further show that the effect is stronger for firms participating in joint ventures and R&D agreements that require a higher commitment from partners. Also, the effect of centrality on leverage is stronger for financially constrained firms, but the effect on investment-price sensitivity is stronger for financially unconstrained firms. Finally, a quasi-natural experiment using state-level variations in corporate income reporting requirements provides further evidence to pin down the direction of causalities from partnership networks to corporate decisions.

Overall, this paper reveals a new aspect of the interaction between corporate policies and product market activities. In addition to a vast volume of research on supply chains and industry structures as determinants of corporate decisions, my research shows that partnerships can also affect corporate policies. This paper also adds to a recently emerging literature on the network analysis in financial economics by presenting a broad picture of partnership networks as well as an application of Bonacich measure to exploit substantial time-series variations in network characteristics. Finally, this paper suggests that it should be a subsequent, fruitful research agenda to study considerable heterogeneity in partnership participants and activities to expand our understanding of the effect of partnerships on a number of topics in corporate finance.

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Table 1

Partnership Characteristics

This table shows the characteristics of partnership deals announced between 1990 and 2013. A partnership deal includes at least two participants. Panel A presents the number of announced deals, the number of total and U.S. participants, the number of U.S. initial public offerings (IPOs: from Jay R. Ritter's website), and the number of U.S. firms in the Compustat/CRSP merged database. Panel A also reports the ratio of the number of deals to the number of U.S. IPOs for three-year moving windows. Panel B shows the number and the proportion of partnership activities classified by SDC, where categories are not mutually exclusive.

Panel A: Partnership Trends

Year	Deals Announced	Total Participants	U.S. Participants	U.S. IPOs	(3) / (4): 3-year	U.S. Firms in Compustat/CRSP database
	(1)	(2)	(3)	(4)	(5)	(6)
1990	3,030	3,574	1,663	110	N/A	5,834
1991	5,321	5,972	2,562	286	N/A	5,986
1992	5,451	6,245	2,617	412	8.47	6,313
1993	6,090	7,441	2,810	509	6.62	7,013
1994	7,204	8,845	3,419	403	6.68	7,357
1995	7,716	9,866	3,561	461	7.13	7,472
1996	4,710	6,440	2,498	677	6.15	7,898
1997	6,212	8,131	3,258	474	5.78	7,870
1998	7,192	9,495	3,761	281	6.65	7,486
1999	8,188	10,220	4,295	477	9.18	7,242
2000	9,851	11,754	4,430	381	10.96	6,909
2001	6,357	8,494	2,969	79	12.48	6,258
2002	4,630	6,721	2,512	66	18.84	5,886
2003	4,705	6,739	3,368	63	42.54	5,643
2004	3,929	5,888	3,016	173	29.46	5,622
2005	4,653	7,079	3,452	159	24.90	5,558
2006	4,581	7,002	3,403	157	20.19	5,465
2007	5,333	8,082	3,230	159	21.23	5,369
2008	5,114	7,888	2,632	21	27.49	5,055
2009	2,190	3,634	1,006	41	31.08	4,781
2010	1,360	2,313	582	91	27.58	4,620
2011	2,881	4,547	1,127	81	12.75	4,534
2012	3,703	5,986	2,066	93	14.25	4,462
2013	3,091	5,064	1,537	157	14.29	4,522

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

Table 2

Network Characteristics

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

Panel A: Network Statistics				
Year	Nodes	Edges	Average Degree	Average Clustering Coefficient
1994	22,373	36,549	3.267	0.463
1995	26,854	43,459	3.237	0.473
1996	27,210	42,923	3.155	0.473
1997	28,737	44,657	3.108	0.478
1998	30,634	45,581	2.976	0.468
1999	32,068	45,683	2.849	0.440
2000	34,030	49,700	2.921	0.427
2001	35,733	51,363	2.875	0.416
2002	34,982	48,710	2.785	0.403
2003	33,195	44,712	2.841	0.391
2004	30,149	38,754	2.571	0.365
2005	26,432	29,026	2.196	0.320
2006	25,240	25,837	2.047	0.285
2007	26,260	25,991	1.980	0.263
2008	27,354	26,466	2.118	0.277
2009	25,914	24,722	1.908	0.288
2010	22,670	21,074	1.859	0.294
2011	20,933	19,371	1.851	0.320
2012	19,362	18,054	1.865	0.370
2013	16,906	15,877	1.878	0.401
Total	547,036	698,509	2.514	0.381

Panel B: Centrality Statistics								
Year	Nodes	Mean	Std.	Min	Median	99th	Max	Skewness
1994	22,373	9.50	35.82	1.00	2.07	117.71	1,535.19	15.40
1995	26,854	9.27	35.69	1.00	2.07	114.71	1,626.00	16.56
1996	27,210	8.93	34.14	1.00	2.05	106.98	1,587.14	17.18
1997	28,737	8.57	32.63	1.00	2.05	100.76	1,470.26	17.16
1998	30,634	7.91	30.52	1.00	2.04	91.83	1,302.98	17.30
1999	32,068	7.48	29.07	1.00	2.01	89.93	1,358.34	18.27
2000	34,030	7.82	32.44	1.00	1.97	101.79	1,415.29	18.62
2001	35,733	7.61	32.03	1.00	1.79	101.49	1,453.53	19.07
2002	34,982	7.15	30.32	1.00	1.58	93.98	1,360.35	19.15
2003	33,195	6.70	28.28	1.00	1.43	87.17	1,233.84	19.16
2004	30,149	6.04	24.71	1.00	1.32	78.45	985.30	19.08
2005	26,432	4.67	16.38	1.00	1.24	53.92	704.62	18.73
2006	25,240	3.91	12.45	1.00	1.22	41.43	631.61	19.39
2007	26,260	3.66	10.68	1.00	1.22	37.94	673.55	20.98
2008	27,354	3.47	9.82	1.00	1.20	35.02	620.55	20.50
2009	25,914	3.40	9.49	1.00	1.19	32.60	543.14	18.98
2010	22,670	3.39	9.18	1.00	1.16	34.87	413.66	15.31
2011	20,933	3.37	9.24	1.00	1.13	33.78	337.41	14.33
2012	19,362	2.82	6.66	1.00	1.09	26.33	209.36	12.02
2013	16,906	2.84	6.48	1.00	1.10	26.30	224.50	11.85
Total	547,036	6.17	25.56	1.00	1.49	74.66	1,626.00	21.23

Table 3

Top 25 Most Central U.S. Firms in Partnership Networks between 1994 and 2013

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

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

Table 4

Descriptive Statistics

Panel A presents the summary statistics for variables used in my empirical tests. The sample consists of 31,827 U.S. firm-year observations in partnership networks between 1994 and 2013. See the Appendix 1 for the complete list of variable definitions. All dollar denominated variables are deflated to 2009 dollars using U.S. GDP deflator. All variables are winsorized at the 1st and 99th percentiles, except for *Centrality*, *Size*, *Age*, and *Dividend Payer*. Panel B shows the correlation coefficients between *Centrality* and a group of key variables in this paper. Panel C shows the correlation between partnership types and activities that are not mutually exclusive (total can exceed 100%).

Panel A: Summary Statistics

	N	Mean	Std.	Min	Median	Max
Partnership Variables						
Centrality	31,827	1.5638	1.4121	0	1.2568	7.3939
Dependent Variables						
Book Leverage	31,827	0.2163	0.2248	0	0.1699	1.1139
Market Leverage	31,827	0.1446	0.1624	0	0.0921	0.6855
CAPEX	31,827	0.0578	0.0696	0	0.0357	0.4261
R&D	22,517	0.1225	0.1571	0	0.0714	0.8785
Controls						
Size (log, million dollars)	31,827	5.7447	2.2924	-2.9145	5.6207	13.5820
Age (years)	31,827	19.3310	15.3621	3	13	64
Q	31,827	2.3207	1.9055	0.6404	1.6723	11.9179
ROA	31,827	0.0281	0.2513	-1.168	0.1002	0.3680
SG&A	31,827	0.3125	0.2851	0	0.2497	1.4500
Tangibility	31,827	0.2296	0.2065	0.0088	0.1604	0.8727
Dividend Payer	31,827	0.2868	0.4523	0	0	1
CF Volatility	31,827	0.1622	0.2529	0.0082	0.0710	1.6260
Asset Growth	31,827	0.1966	0.6066	-0.5812	0.0625	3.8784

Panel B: Correlation Matrix of Key Variables									
Number of Observations: 31,827									
	Centrality	Size	Age	Q	ROA	CAPEX	R&D	Risk	Book Leverage
Centrality	1								
Size	0.2998	1							
Age	0.0829	0.5347	1						
Q	0.0940	-0.2267	-0.2148	1					
ROA	0.0390	0.4868	0.3000	-0.2525	1				
CAPEX	0.0031	0.0359	-0.0658	0.0152	0.0767	1			
R&D	0.0896	-0.3966	-0.2675	0.3846	-0.6456	-0.0951	1		
Risk	-0.0689	-0.6041	-0.4398	0.1091	-0.4972	-0.0295	0.3108	1	
Book Leverage	-0.0542	0.2391	0.1317	-0.1572	0.0562	0.1308	-0.2004	-0.0447	1

Panel C: Correlation Matrix of Partnership Activities					
Number of Observations: 31,827					
	Joint Venture	Licensing Agreement	R&D Agreement	Manufacturing Agreement	Marketing Agreement
Joint Venture	1				
Licensing Agreement	-0.0289	1			
R&D Agreement	0.0590	0.3297	1		
Manufacturing Agreement	0.2935	0.2325	0.2324	1	
Marketing Agreement	0.0648	0.2869	0.2597	0.2028	1

Table 5

Partnership Network Centrality and Leverage

This table shows the effect of centrality in partnership networks on corporate leverage. Dependent variables are indicated in the header of each column. *Centrality* is a natural logarithm of the Bonacich centrality described in Section 3.2. For all other variables, see the Appendix 1 for the complete list of variable definitions. Industry fixed-effects are based on SIC 4-digit industries. 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	Book Leverage	Book Leverage	Market Leverage	Market Leverage
	(1)	(2)	(3)	(4)
Centrality	**-0.012*** **	**-0.002**	**-0.007*** **	**-0.000**
	(-6.485)	**(-1.258)**	**(-7.014)**	**(-0.382)**
Controls				
Size	0.025***	0.014***	0.012***	0.025***
	(14.249)	(3.734)	(10.511)	(10.855)
Age	0.001	0.042***	-0.018***	0.013**
	(0.253)	(4.607)	(-7.577)	(2.282)
Q	-0.003*	-0.004***	-0.012***	-0.006***
	(-1.953)	(-3.989)	(-22.321)	(-13.356)
CAPEX	-0.195***	-0.001	-0.113***	0.015
	(-4.325)	(-0.019)	(-3.891)	(0.677)
Tangibility	0.289***	0.141***	0.169***	0.082***
	(13.646)	(5.365)	(11.684)	(4.745)
ROA	-0.163***	-0.101***	-0.078***	-0.060***
	(-11.443)	(-6.920)	(-11.409)	(-8.112)
CF Volatility	0.007	0.052**	0.011**	0.029***
	(0.559)	(2.482)	(1.963)	(3.093)
SG&A	0.008	-0.013	-0.020***	-0.007
	(0.712)	(-0.927)	(-3.860)	(-1.128)
R&D	-0.116***	-0.043	-0.100***	-0.030**
	(-4.348)	(-1.329)	(-8.162)	(-2.152)
Dividend Payer	-0.048***	0.001	-0.038***	0.000
	(-7.887)	(0.177)	(-9.572)	(0.113)
Industry Median Leverage	-0.000	0.000	0.369***	0.248***
	(-1.201)	(0.333)	(18.099)	(14.027)
Initial Leverage	0.101***		0.290***	
	(8.535)		(20.249)	
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
Observations	31,827	31,827	31,827	31,827
R^2	0.306	0.734	0.463	0.779

Table 6

Partnership Network Centrality and Investment-Price Sensitivity

This table shows the effect of centrality in partnership networks on the sensitivity of investment to prices. The measure of investment is indicated in the header of each column. *Centrality* is a natural logarithm of the Bonacich centrality described in Section 3.2. For all other variables, see the Appendix 1 for the complete list of variable definitions. Industry fixed-effects are based on SIC 4-digit industries. 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		R&D		CAPEX + R&D	
	(1)	(2)	(3)	(4)	(5)	(6)
Centrality	0.001	0.000	0.009***	0.005***	0.011***	0.006***
	(1.152)	(0.536)	(7.126)	(3.971)	(7.287)	(3.974)
Q	0.009***	0.008***	0.018***	0.014***	0.026***	0.022***
	(15.660)	(14.264)	(13.994)	(12.731)	(18.412)	(16.580)
Centrality × Q	**-0.001****	**-0.001****	**-0.001***	**-0.001***	**-0.001*****	**-0.001*****
	(-2.251)	**(-2.471)**	**(-1.748)**	**(-1.744)**	**(-2.691)**	**(-2.864)**
Sales Growth	0.004***	-0.000	-0.001	-0.002	0.001	-0.002
	(3.628)	(-0.003)	(-0.509)	(-1.039)	(0.497)	(-0.610)
Centrality × Sales Growth	0.001	0.001**	0.002	0.002*	0.002*	0.002**
	(0.888)	(2.018)	(1.604)	(1.813)	(1.670)	(1.964)
ROA	0.041***	0.030***	-0.203***	-0.121***	-0.173***	-0.097***
	(11.240)	(7.289)	(-16.806)	(-10.042)	(-13.273)	(-7.400)
Centrality × ROA	-0.000	0.001	0.004	0.001	0.007	0.005
	(-0.172)	(0.823)	(0.902)	(0.252)	(1.471)	(1.030)
Size	-0.001***	-0.012***	-0.009***	-0.048***	-0.010***	-0.059***
	(-2.901)	(-10.906)	(-10.150)	(-18.814)	(-9.886)	(-19.656)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	No	No	Yes	No
Firm FE	No	Yes	Yes	Yes	No	Yes
Observations	31,827	31,827	22,517	22,517	22,517	22,517
R^2	0.370	0.688	0.571	0.676	0.861	0.813

Table 7

Subsample Analysis: Partnership Types

This table shows the effect of joint ventures (Panel A) and R&D agreements (Panel B) on the relationship between the centrality in partnership networks and corporate leverage (Columns 1–4) and investment-price sensitivity (Columns 5–10). Dependent variables are indicated in the header of each column. *Joint Venture* indicates whether a firm participates in at least one joint venture, 0 otherwise. *R&D Agreement* indicates whether a firm participates in at least one R&D agreement. *Centrality* is a natural logarithm of the Bonacich centrality described in Section 3.2. *Controls* include all control variables shown in Table 5 (leverage) and Table 6 (investment-price sensitivity). Industry fixed-effects are based on SIC 4-digit industries. Only the coefficients of interest are reported for a parsimony. Standard errors are corrected for heteroskedasticity and clustering at the firm level. *t*-statistics are in parentheses. See Table 4 for the list of winsorized variables. ***, **, and * indicate the statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Joint Venture										
Dep. Variable	Book Leverage		Market Leverage		CAPEX		R&D		CAPEX + R&D	
Joint Venture	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Centrality	**-0.011*****	**-0.008*****	**-0.009*****	**-0.005*****						
	(-4.095)	**(-3.366)**	**(-4.983)**	**(-3.827)**						
Centrality × Q					**-0.002*****	**-0.000**	**-0.001**	**-0.001**	**-0.003*****	**-0.001***
					(-3.733)	**(-1.372)**	**(-1.602)**	**(-1.078)**	**(-2.749)**	**(-1.784)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,615	19,212	12,615	19,212	12,615	19,212	7,865	14,652	7,865	14,652
R^2	0.357	0.292	0.485	0.449	0.416	0.358	0.583	0.550	0.511	0.487

Panel B: R&D Agreement										
Dep. Variable	Book Leverage		Market Leverage		CAPEX		R&D		CAPEX + R&D	
R&D Agreement	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Centrality	**-0.016*** **	**-0.007*** **	**-0.009*** **	**-0.005*** **						
	(-5.233)	**(-2.996)**	**(-4.750)**	**(-3.890)**						
Centrality × Q					**-0.000**	**-0.001** **	**-0.003*** **	**0.000**	**-0.003*** **	**-0.000**
					(-0.348)	**(-2.441)**	**(-4.571)**	**(0.557)**	**(-4.262)**	**(-0.490)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,629	20,198	11,629	20,198	9,836	21,991	8,588	13,929	8,588	13,929
R^2	0.288	0.338	0.440	0.479	0.300	0.419	0.585	0.535	0.522	0.440

Table 8

Subsample Analysis: Financial Constraints

This table shows the effect of financial constraints on the relationship between the centrality in partnership networks and corporate leverage (Panel A) and investment-price sensitivity (Panel B). Dependent variables are indicated in the title of each panel. *FC Measure* indicates the measure of financial constraints for each column where *high* (*low*) implies financially constrained (unconstrained) samples, and vice versa. *High* and *Low* are determined at the 67th and 33rd percentiles of each measure, respectively. *Centrality* is a natural logarithm of the Bonacich centrality described in Section 3.2. *Controls* include all control variables shown in Table 5 (leverage) and Table 6 (investment-price sensitivity) in accordance with dependent variables. Industry fixed-effects are based on SIC 4-digit industries. Only the coefficients of interest are reported for a parsimony. Standard errors are corrected for heteroskedasticity and clustering at the firm level. *t*-statistics are in parentheses. See Table 4 for the list of winsorized variables. ***, **, and * indicate the statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Centrality and Leverage						
FC Measure	WW Index: High	WW Index: Low	KZ Index: High	KZ Index: Low	SA Index: High	SA Index: Low
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Book Leverage						
Centrality	**-0.010*** **	**-0.007** **	**-0.008** **	**-0.003** **	**-0.011*** **	**-0.004**
	(-3.276)	**(-2.535)**	**(-2.341)**	**(-2.279)**	**(-3.715)**	**(-1.419)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,503	10,503	10,503	10,503	10,503	10,503
R^2	0.247	0.448	0.292	0.475	0.255	0.425
Dependent Variable: Market Leverage						
FC Measure	WW Index: High	WW Index: Low	KZ Index: High	KZ Index: Low	SA Index: High	SA Index: Low
	(1)	(2)	(3)	(4)	(5)	(6)
Centrality	**-0.006*** **	**-0.004** **	**-0.008*** **	**-0.002*** **	**-0.006*** **	**-0.003***
	(-3.932)	**(-2.195)**	**(-4.122)**	**(-2.726)**	**(-4.152)**	**(-1.805)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,503	10,503	10,503	10,503	10,503	10,503
R^2	0.247	0.448	0.292	0.475	0.255	0.425

Panel B: Centrality and Investment-Price Sensitivity						
FC Measure	WW Index: High	WW Index: Low	KZ Index: High	KZ Index: Low	SA Index: High	SA Index: Low
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: CAPEX						
Centrality × Q	**-0.001**	**-0.001***	**-0.001****	**-0.001**	**-0.000**	**-0.001***
	(-1.268)	**(-2.266)**	**(-2.079)**	**(-1.206)**	**(-0.515)**	**(-1.856)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,503	10,503	10,503	10,503	10,503	10,503
R^2	0.247	0.448	0.292	0.475	0.255	0.425
Dependent Variable: R&D						
Centrality × Q	**-0.000**	**-0.001**	**-0.001**	**-0.002***	**-0.000**	**-0.001**
	(-0.271)	**(-1.518)**	**(-0.900)**	**(-1.767)**	**(-0.570)**	**(-1.389)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,486	6,594	6,710	8,127	8,455	6,652
R^2	0.510	0.614	0.615	0.526	0.498	0.563
Dependent Variable: CAPEX + R&D						
Centrality × Q	**-0.001**	**-0.002****	**-0.001***	**-0.002***	**-0.001**	**-0.002***
	(-0.937)	**(-2.486)**	**(-1.870)**	**(-1.954)**	**(-1.084)**	**(-1.746)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,486	6,594	6,710	8,127	8,455	6,652
R^2	0.454	0.549	0.551	0.428	0.435	0.495

Table 9:

Instrument Variable Estimations

This table reports the estimation results of instrument variable regressions. Dependent variables are indicated in the header of each column. *Centrality* is a natural logarithm of the Bonacich centrality described in Section 3.2. *Controls* include all control variables shown in Table 5 (leverage) and Table 6 (investment-price sensitivity) in accordance with dependent variables. All specifications estimate a two-stage least squares (2SLS) model using *Combined Reporting* as an instrument variable for *Centrality* at the first stage. 2SLS estimations include calendar year and industry fixed-effects based on SIC 2-digit industries. The Kleibergen-Paap rk LM Statistic tests whether the excluded instruments are relevant with the endogenous regressors. The test of endogeneity examines whether the endogenous regressors are in fact exogenous given the instruments. Only the coefficients of interest are reported for a parsimony. Standard errors are corrected for heteroskedasticity and clustering at the firm level. *t*-statistics are in parentheses. See Table 4 for the list of winsorized variables. ***, **, and * indicate the statistical significance at 1%, 5%, and 10%, respectively.

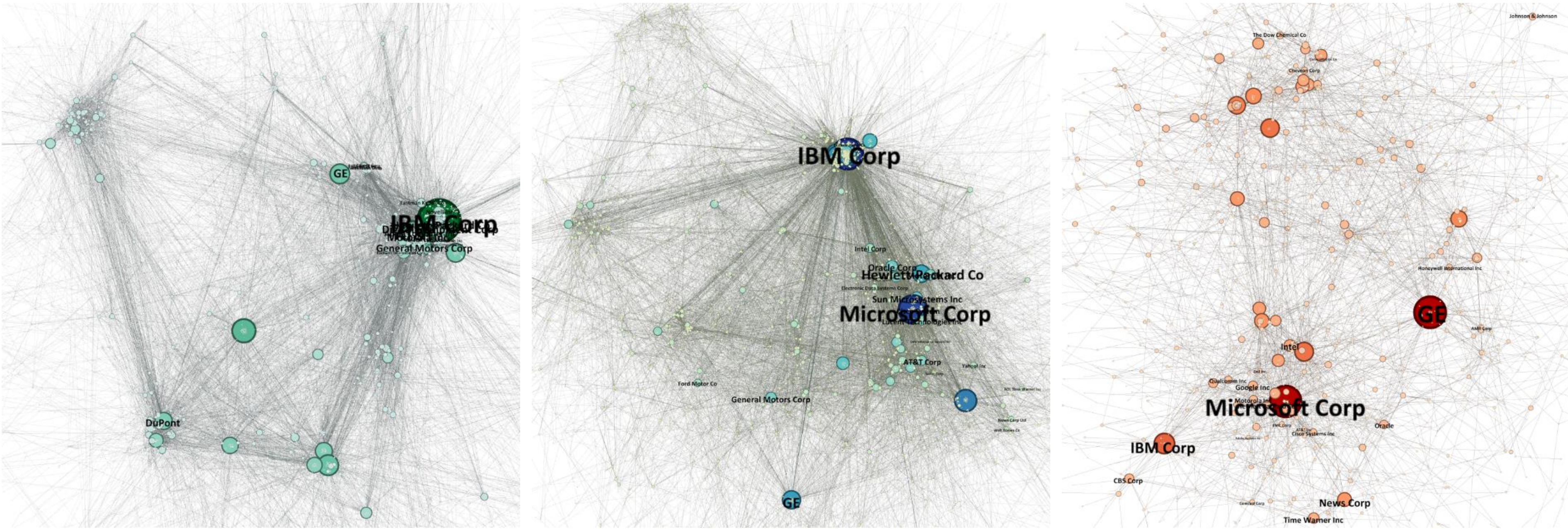
Dependent Variable	Book Leverage	Market Leverage	CAPEX	R&D	CAPEX + R&D
	(1)	(2)	(3)	(4)	(5)
Centrality	**-0.150*** **	**-0.079** **			
	(-3.64)	**(-2.84)**			
Centrality × Q			**-0.004* **	**0.010**	**0.005**
			(-1.69)	**(0.64)**	**(0.39)**
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM Statistic	22.32***	18.78***	3.83***	0.62	0.62
Test of Endogeneity	20.12***	2.74*	5.84***	35.20***	23.25***
Observations	11,308	11,308	11,308	7,634	7,634

Table 10

Valuation Effects

This table shows the effect of centrality in partnership networks on corporate valuations. Dependent variable is Tobin's Q. *Centrality* is a natural logarithm of the Bonacich centrality described in Section 3.2. For all other variables, see the Appendix 1 for the complete list of variable definitions. Column (1) estimates an OLS model with calendar year and industry fixed-effects based on SIC 4-digit industries. Column (2) estimates a two-stage least squares (2SLS) model using *Combined Reporting* as an instrument variable for *Centrality* at the first stage. 2SLS estimations include calendar year and industry fixed-effects based on SIC 2-digit industries. 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	Q	Q
	(1)	(2)
Centrality	**0.116*** **	**0.557** **
	(7.094)	**(2.348)**
Controls		
Delaware	0.032	0.016
	(0.832)	(0.255)
Size	-0.051***	-0.182
	(-3.755)	(-1.538)
Age	-0.164***	-0.335***
	(-5.275)	(-8.060)
ROA	-0.062	2.181***
	(-0.447)	(5.887)
R&D	3.203***	3.694***
	(11.263)	(3.322)
Book Leverage	-0.459***	-0.460*
	(-3.998)	(-1.828)
CAPEX	3.349***	3.238***
	(9.772)	(5.809)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Kleibergen-Paap rk LM Statistic		27.29***
Test of Endogeneity		4.39**
Observations	31,827	11,308



(A) Network in 1994

Number of nodes: 22,373

(B) Network in 2002

Number of nodes: 34,982

(C) Network in 2010

Number of nodes: 22,670

Figure 1

Snapshot of Partnership Networks

This figure illustrates the snapshot of partnership networks for selected years. Each illustration consists of points (nodes) and lines (edges). I use Gephi 0.8.2 to visualize networks with the “OpenOrd” layout specialized in distinguishing clusters in undirected graphs. The size of points indicates the degree (the number of direct connections) of each node. Each snapshot shows the location of 25 key firms in networks listed in Table 3.

Appendix 1

Variable Definitions

Variables	Description	Source
Centrality	A natural logarithm of the Bonacich centrality. See the Appendix 2 for an introduction of the Bonacich centrality.	SDC
Book Assets	Total Assets (**at**)	Compustat
Size	A natural logarithm of Book Assets, deflated to 2009 dollars using U.S. GDP deflator from Bureau of Economic Analysis	
Age	A natural logarithm of the firm age, defined as 1 plus the number of years appearing in Compustat	
Total Debt	Short-term Debt (**dlc**) + Long-term Debt (**dltt**)	
Book Leverage	Total Debt / Book Assets	
Market Value of Assets	Total Assets (**at**) – Common Equity (**ceq**) + [Common Share Price (**prcc_f**) * Common Shares Outstanding (**csho**)]. If **prcc_f** is missing, I use the price (**prc**) at the last trading date of the fiscal year from CRSP.	
Market Leverage	Total Debt / Market Value of Assets	
Industry Med. Leverage	Median of leverage within the same SIC 3-digit industry. For 2SLS estimations, I use SIC 2-digit industry classfications.	
Initial Leverage	The first non-missing value of leverage from Compustat. For firms that appeared in Compustat before 1990 when my partnership data begins, I use the leverage in 1990 to proxy the initial leverage.	
Q	Market Value of Assets / Book Assets	
Tangibility	Net Property, Plants, and Equipment (**ppent**) / Total Assets (**at**)	
ROA	Operating Income Before Depreciation and Amortization (**oibdp**) / Total Assets (**at**)	
SG&A	Sales, General, and Administrative Expenses (**xsga**) / Total Assets (**at**).	
R&D	Research and Development Expenditure (**xrd**) / Total Assets (**at**). For the investment regression, **xrd** is scaled by the lagged Total Assets ($\mathbf{at}_{-1}$).	
CAPEX	Capital Expenditure (**capx**) / Total Assets (**at**). For the investment regression, **capx** is scaled by the lagged Total Assets ($\mathbf{at}_{-1}$).	
Asset Growth	Change in Total Assets ($\mathbf{at} - \mathbf{at}_{-1}$)/ lagged Total Assets ($\mathbf{at}_{-1}$)	

Sales Growth	Change in Sales (**sale** – **sale**$_{-1}$)/ lagged Sales (**sale**$_{-1}$)	
CF Volatility	Standard deviation of cash flows for the previous 10 years. I require at least three observations.	
Dividends	Common Dividends (**dvc**) / Total Assets (**at**)	
Dividend Payer	An indicator variable which equals 1 if Dividends > 0, 0 otherwise	
WW Index	Whited and Wu (2006): -0.091 * CF – 0.062 * Dividend Payer + 0.021 * Long-term Debt (**dltt/at**) – 0.044 * Size + 0.102 * Industry Sales Growth (SIC 3-digit) – 0.035 * Firm Sales Growth	
KZ Index	Lamont, Polk and Saá-Requejo (2001): –1.001909 * CF + 0.2826389 * Q + 3.139193 * Book Leverage – 39.3678 * Dividends – 1.314759 * Cash	
SA Index	Hadlock and Pierce (2010): –0.737 * Total Assets + 0.043 * Total Assets^2 – 0.04 * (1 + the number of years appearing in Compustat). Total Assets are deflated to 2009 dollars using U.S. GDP deflator from BEA.	
SIC	SIC industry classifications. I primarily use the Compustat historical SIC code (**sich**). I use the first non-missing **sich** for the all prior fiscal years with missing **sich**. If **sich** is still missing, I use the CRSP historical SIC code (**siccd**).	
Delaware	An indicator variable which equals 1 if a firm is incorporated in the State of Delaware, 0 otherwise. I use the variable **incorp** from Compustat.	
Combined Reporting	Bodnaruk, Massa and Simonov (2013): Average of subsidiary-level combined reporting indicator variables within the same SIC 4-digit industry (excluding the firm itself from the computation). For each subsidiary of firm, a combined reporting indicator variable equals 1 if the subsidiary is operated in the state that requires combined reporting rules for corporate income taxes, 0 otherwise.	Compustat Dun & Bradstreet

Appendix 2

Robustness to Centrality Measures

This appendix introduces the idea and mathematical formulation of the Bonacich centrality, and presents the robustness of empirical results using variations of centrality measures. See Chapter 2 of Jackson (2008) for more general introductions of centrality measures.

Consider a network consists of n different nodes. Let denote $\boldsymbol{G}$ as an $n \times n$ adjacency matrix which has an element of unity if two nodes are connected, and zero otherwise. Also denote $\boldsymbol{1}$ as an $n \times 1$ vector of ones. Define a walk as a direct connection from one to another node in the network. Then $\boldsymbol{G1}$ indicates the number of walks emanating from each node, i.e., the degree of each node. Furthermore, $\boldsymbol{GG1} = \boldsymbol{G}^2\boldsymbol{1}$ 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 $\boldsymbol{G}^2\boldsymbol{1}$ is 2, then Node 3 can reach two other nodes in the network via two walks, such as (3 → 1 → 2) and (3 → 4 → 1). Likewise, $\boldsymbol{G}^k\boldsymbol{1}$ indicates the number of indirect connections from each node where an indirect connection consists of k walks.

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

$$\boldsymbol{P} = \boldsymbol{G1} + \beta\boldsymbol{G}^2\boldsymbol{1} + \beta^2\boldsymbol{G}^3\boldsymbol{1} + \cdots \tag{A1}$$

$$\boldsymbol{P} = (\boldsymbol{1} + \beta\boldsymbol{G} + \beta^2\boldsymbol{G}^2 + \cdots)\boldsymbol{G1} = (\boldsymbol{I} - \beta\boldsymbol{G})^{-1}\boldsymbol{G1} \tag{A2}$$

Notice that $\boldsymbol{P}$ is well-defined for a sufficiently small β.

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

$$\boldsymbol{C} = \alpha\boldsymbol{P} = \alpha(\boldsymbol{I} - \beta\boldsymbol{G})^{-1}\boldsymbol{G1} \tag{A3}$$

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

In my main empirical tests, I follow earlier guidelines for the choice of β (Robinson and Stuart 2007b) and set β equal to three-quarters of the reciprocal of the largest eigenvalue of $\boldsymbol{G}$. It should be emphasized that any parametrization of the Bonacich centrality preserves the ordinal ranking of centrality within a network, to the extent that β is sufficiently small so that the measure is well-defined. For the robustness of results, I additionally create two Bonacich centrality measures with one higher and one lower β than the one I use in the paper. These measures are named "Bonacich+" and "Bonacich-". Specifically, Bonacich+ (Bonacich-) takes 120% (80%) of the value for β in my main empirical tests. The upper bound is set to 120% that provides well-defined Bonacich measure across all networks.

Table A2-1 summarizes the logarithm of four different centrality measures tested for the robustness of results: Bonacich+, Bonacich-, degree, and eigenvector centrality. Panel A confirms that Bonacich measures capture the indirect connections to which the degree centrality is unable. Both the mean and the standard deviation of centrality monotonically increase, showing an increase in the value of indirect connections (from zero in the degree centrality to the largest in Bonacich+). The magnitude of eigenvector centrality is considerably lower than other measures, since it is normalized to set the length of centrality vector equal to the unity. Panel B shows that all of centrality measures are highly correlated. This result is unsurprising as these measures are designed to capture the essence of network positions: the status of connections in the networks.

Table A2-1

Summary of Centrality Measures

Panel A: Descriptive Statistics						
	N	Mean	Std.	Min	Median	Max
Degree	31,827	0.9963	1.0438	0	0.6931	6.3509
Bonacich- (0.8β)	31,827	1.3909	1.2728	0	1.1402	6.9879
Bonacich	31,827	1.5638	1.4121	0	1.2568	7.3939
Bonacich+ (1.2β)	31,827	1.9096	1.7054	0	1.5112	8.2484
Eigenvector	31,827	0.0032	0.0126	0	0.0001	0.3815

Panel B: Correlation Matrix					
	Bonacich	Bonacich+	Bonacich-	Degree	Eigenvector
Bonacich	1				
Bonacich+	0.9910	1			
Bonacich-	0.9955	0.9742	1		
Degree	0.8944	0.8363	0.9302	1	
Eigenvector	0.5457	0.5301	0.5501	0.5293	1

Table A2-2

Robustness to Centrality Measures

This table reports the robustness of main results (Section 4.1) under the difference choice of centrality measures: Bonacich+, Bonacich-, degree, and eigenvector centrality. Only the coefficients of interest are reported for a parsimony. See Appendix 2 for the details of centrality measures. *Controls* include all control variables shown in Table 5 (leverage) and Table 6 (investment-price sensitivity). All specifications include calendar year and industry fixed-effects based on SIC 4-digit industries. 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: Centrality and Leverage				
Dependent Variable: Book Leverage				
Centrality measure	Bonacich+	Bonacich-	Degree	Eigenvector
Centrality	**-0.009*** **	**-0.013*** **	**-0.015*** **	**-0.839*** **
	(-6.374)	**(-6.520)**	**(-6.226)**	**(-3.488)**
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	31,827	31,827	31,827	31,827
R^2	0.306	0.306	0.306	0.305
Dependent Variable: Market Leverage				
Centrality measure	Bonacich+	Bonacich-	Degree	Eigenvector
Centrality	**-0.006*** **	**-0.008*** **	**-0.009*** **	**-0.383*** **
	(-6.898)	**(-7.012)**	**(-6.277)**	**(-3.059)**
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	31,827	31,827	31,827	31,827
R^2	0.306	0.306	0.306	0.305

Panel B: Centrality and Investment-Price Sensitivity				
Dependent Variable: CAPEX				
Centrality measure	Bonacich+	Bonacich-	Degree	Eigenvector
Centrality × Q	**-0.000****	**-0.001****	**-0.001***	**-0.061*****
	(-2.190)	**(-2.239)**	**(-1.938)**	**(-2.578)**
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	31,827	31,827	31,827	31,827
R^2	0.370	0.370	0.370	0.371
Dependent Variable: R&D				
Centrality measure	Bonacich+	Bonacich-	Degree	Eigenvector
Centrality × Q	**-0.001***	**-0.001**	**-0.001**	**-0.157*****
	(-1.784)	**(-1.643)**	**(-0.847)**	**(-6.659)**
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	22,517	22,517	22,517	22,517
R^2	0.571	0.570	0.570	0.569
Dependent Variable: CAPEX + R&D				
Centrality measure	Bonacich+	Bonacich-	Degree	Eigenvector
Centrality × Q	**-0.001*****	**-0.002*****	**-0.001***	**-0.221*****
	(-2.618)	**(-2.648)**	**(-1.904)**	**(-6.567)**
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	22,517	22,517	22,517	22,517
R^2	0.497	0.496	0.495	0.495

Appendix 3

List of States with Combined Reporting

This 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		