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Being central is a double-edged sword: Knowledge network centrality and new product development in U.S. pharmaceutical industry

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ABSTRACT

Today firms extensively use external knowledge from interfirm knowledge networks for their new product development (NPD). In light of this phenomenon, scholars and managers often believe that a higher centrality in interfirm knowledge networks is good for absorbing external knowledge and improving NPD performance. Since knowledge network centrality can be measured from different perspectives, however, we propose that some types of centrality might do more harm than good for NPD. Using a panel data set from the U.S. pharmaceutical industry, we empirically examine the impacts of three measures for knowledge network centrality (i.e., degree centrality, closeness centrality and eigenvector centrality) on NPD performance. We find that degree centrality in an interfirm knowledge network is positively associated with subsequent NPD performance. Counter-intuitively, closeness centrality and eigenvector centrality in an interfirm knowledge network have negative impacts on subsequent NPD performance. Taken together, our findings remind the danger of oversimplifying the complex impact of knowledge network centrality on innovation.

1. Introduction

> *"There is certainly no unanimity on exactly what centrality is or on its conceptual foundations, and there is very little agreement on the proper procedure for its measurement."*— Freeman (1977: 217)

The burgeoning innovation literature has revealed the interest of firms in tapping into external knowledge, and has begun to understand the outside-in knowledge flows that occur as part of this, depicting that firms rely on knowledge networks to assimilate external knowledge (Dong and Yang, 2015). Knowledge networks provide ample external knowledge resources to a focal firm by allowing recombinant opportunities and innovation such as new products and services. In particular, innovation studies on new product development (NPD) suggest that firms need to be open to external knowledge resources when they search for innovation (e.g., Ancona and Caldwell, 1992; Barczak et al., 2009). On the other hand, network researchers similarly emphasize the importance for firms to assimilate external knowledge from interfirm networks to benefit their NPD activities (e.g., Krackhardt and Hanson, 1993; Tsai, 2001).

Prior innovation studies on interfirm networks have been mainly focusing on collaboration networks based on alliance partnerships (e.g., Durmusoglu, 2013; Gilsing et al., 2008, 2014; Srivastava et al., 2015; Stolwijk et al., 2013; Vanhaverbeke et al., 2012). However, knowledge networks are different from collaboration networks, as the latter are actually relationship-based rather than knowledge-based. Dong and Yang (2015) was among the first to propose that interfirm knowledge networks are constructed based on knowledge flows embedded in patent citations among firms, whereas interfirm collaboration networks are primarily developed based on alliance partnerships among firms. Within an interfirm knowledge network in an industry, it is possible that knowledge flows occur via organizational learning without formal collaborations among firms (Dong and Yang, 2015). For example, a focal firm can read and learn from another firm's patents without entering into a strategic alliance with it.

Network centrality is thus defined as the extent to which an actor is central in a network, and is among the most important structural properties in network research (Freeman, 1977, 1979). Different centrality measures have been used in network research, including degree, closeness and betweenness centrality (Freeman, 1979), as well as the more sophisticated eigenvector centrality (Bonacich, 1972). Each of these centrality measures is conceptualized and measured from different perspectives, and thereby captures the meaning of a central position in the network in different ways. In an interfirm knowledge network, however, whether different types of centrality are all good for NPD has not been examined. Given the importance of interfirm knowledge network

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for NPD, we examine how different centrality measures influence NPD performance in the U.S. pharmaceutical industry. We pay particular attention to degree centrality, closeness centrality and eigenvector centrality, as betweenness centrality is not that relevant to interfirm knowledge networks.[1]

Intuitively, scholars and managers often believe that a central position in an interfirm knowledge network can facilitate the assimilation of external knowledge for NPD, implying that knowledge network centrality must be good. While external knowledge is admittedly useful for developing new products, exposure to excessive knowledge that may or may not be relevant to NPD can make it difficult to focus on the most pertinent knowledge and can thus be counterproductive (Cyert and March, 1963; Greve, 2003). Moreover, it is not only the knowledge itself that matters, as the provider of the knowledge also plays a role in determining the usefulness of knowledge. In an interfirm knowledge network, a focal firm's NPD performance not only depends on how much knowledge is acquired from other firms, but also on what kind of knowledge is obtained. Relying on the prominent knowledge from other firms that are central in the interfirm knowledge network can actually become an inhibitor of innovation, due to core rigidities (Leonard-Barton, 1992; Levitt and March, 1988).

In this study, we follow the recent literature using patent citations, rather than alliance partnerships, to construct interfirm knowledge networks for the U.S. pharmaceutical industry over time, because interfirm knowledge networks consist of knowledge flows among firms that can be observed in their patent citations rather than alliance partnerships. Specifically, we construct interfirm knowledge networks over time based on patent citation pairs, and calculate different measures for knowledge network centrality with a panel structure. Relying on objective NPD performance data from new drug approval files, we empirically examine the impacts of a firm's degree centrality, closeness centrality and eigenvector centrality in an interfirm knowledge network on its subsequent NPD performance. Counter-intuitively, we find that industry knowledge centrality is a double-edged sword for NPD performance, as some centrality measures can lead to undesirable innovation outcomes. Degree centrality is positively related to NPD performance in an interfirm knowledge network, whereas closeness centrality and eigenvector centrality are negatively related to NPD performance.

The rest of this paper is organized as follows. Next, we introduce the theoretical background and develop our hypotheses. The methodology is then introduced, followed by the empirical results. Finally, we discuss the theoretical and practical implications of this study, as well as the limitations and directions for future research.

2. Theory and hypotheses

2.1. Theoretical background

Conventionally, the innovation literature has documented that the structural positions of firms in interfirm collaboration networks matters for innovation (Ahuja, 2000; Powell et al., 1996; Walker et al., 1997). Recent innovation studies distinguish collaboration networks and knowledge networks. At the individual level, Wang et al. (2014) noted that knowledge networks embedded in patent citations that fall into the same knowledge domains are different from collaboration networks based on patent co-authorships among inventors in a firm. At the firm level, Guan and Liu (2016) have similarly identified knowledge networks based on patent citations made by firms that fall into the same knowledge domains and collaboration networks based on patent co-authorships among firms. This conceptualization of knowledge networks at the firm level, however, captures the overlap of knowledge domains among firms instead of knowledge flows among firms that are critical for innovation. Dong and Yang (2015) proposed that interfirm knowledge networks are constructed based on knowledge flows embedded in patent citations among firms. Knowledge networks rooted in patent citations have also been conceptualized at the patent level (David et al., 2011; Huenteler et al., 2016; Jee and Sohn, 2015) or at the country level (Nam and Barnett, 2011; Tseng, 2009).

Although interfirm knowledge networks matters for the assimilation of external knowledge (Dong and Yang, 2015), none of prior work has examined the impact of structural positions of firms in interfirm knowledge networks on innovation, such as NPD performance. This is an important gap in our understanding, as whether a central position in an interfirm knowledge network is good for innovation, and, if so, what kind of central position is the most useful remains unclear to researchers and practitioners. In this study, we address this gap by examining the impacts of different measures for knowledge network centrality on NPD performance. Network centrality refers to the extent to which an actor is central in a network (Freeman, 1977, 1979). In the network literature, four different centrality measures have been used, including degree centrality, closeness centrality, eigenvector centrality, and betweenness centrality (Bonacich, 1972; Freeman, 1979). In an interfirm knowledge network, *degree centrality* refers to the number of knowledge ties between a focal firm and other firms that it is directly connected to in the network (Freeman, 1979). If a focal firm has a lot of knowledge ties that it directly gets access to, the firm is central in an interfirm knowledge network in terms of degree centrality.

In an interfirm knowledge network, *closeness centrality* refers to the average shortest distance of knowledge ties between a focal firm and all other firms in the network (Freeman, 1979). Degree centrality reflects the local knowledge ties around a focal firm, while closeness centrality captures the global knowledge ties available in the whole network; firms with a shorter distance to get access to the knowledge held by all other firms in the network are more central in an interfirm knowledge network in terms of closeness centrality. In an interfirm knowledge network, *eigenvector centrality* indicates the degree to which a focal firm's knowledge ties are connected to other firms that are central in the network (Bonacich, 1972). Eigenvector centrality describes the prominent sources of knowledge in the network, and a firm is central in terms of eigenvector centrality if it has knowledge ties to the firms that maintain numerous knowledge ties with others in the network.

In an interfirm collaboration network, *betweenness centrality* represents the degree to which a focal firm has partnership ties connecting two other firms in the network. Therefore, a focal firm with high betweenness centrality in the interfirm collaboration network can bridge and control the information flows from one partner to another, which, however is not that meaningful in the context of an interfirm knowledge network.[2] We thus focus on degree centrality, closeness centrality and eigenvector centrality in an interfirm knowledge network, and hypothesize their different impacts on NPD performance.

2.2. Hypotheses development

The attention-based view of the firm suggests that firms need to conduct problemistic search, which refers to a focused search process directed toward solutions to a specific problem (Cyert and March, 1963; Greve, 2003), in order to effectively and efficiently develop innovation. Otherwise, boundedly rational knowledge workers are likely to be counterproductive, as they have cognitive constraints and suffer from information overload. To obtain better NPD performance, a firm needs to focus on the most pertinent knowledge that is useful for the new products under development, instead of processing all available knowledge. Degree centrality in an interfirm knowledge network reflects the intensity of local knowledge ties directly carrying the knowledge from other firms to a focal firm for recombination, and the corresponding local patent citations capture the most pertinent

[1] To avoid omitted variable bias, we also calculate betweenness centrality and control its impact on NPD performance in the empirical analysis.

[2] We thank one anonymous reviewer who suggested this point.

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knowledge inputs that the firm has used in developing new recombinant, patented knowledge. The more such pertinent knowledge inputs are used in problemistic search, the more new products are likely to be successfully generated later. We thus have the following hypothesis.

H1. A firm's degree centrality in an interfirm knowledge network has a positive effect on its subsequent NPD performance.

Different from degree centrality, closeness centrality in an interfirm knowledge network reflects the global knowledge ties carrying all possible knowledge flows from other firms directly, or indirectly via knowledge flows among other firms, to a focal firm (Opsahl et al., 2010). In particular, indirect knowledge ties in an interfirm knowledge network provide potential technological opportunities for a firm to search. The shorter distance by which a focal firm acquires knowledge from all other firms in the interfirm knowledge network, the more likely that this firm will be overwhelmed by the abundant knowledge it obtains from the network. As effective and efficient search requires focus, exposure to too much knowledge from an interfirm knowledge network can lead to information overload, thereby reducing the likelihood of successfully generating new products. Stated otherwise, with a high closeness centrality a firm can easily get access to all other firms' knowledge and become overwhelmed, leading to lower NPD performance, as expressed in the following hypothesis.

H2. A firm's closeness centrality in an interfirm knowledge network has a negative effect on its subsequent NPD performance.

Eigenvector centrality is different from degree and closeness centrality by emphasizing the importance of others that are connected to a focal firm (Bonacich, 2007). Firms that are central in an interfirm knowledge network are also active in the knowledge exchange that occurs, and by extensively exchanging knowledge with other firms in the network they often accumulate more mature patented knowledge. If a focal firm mainly links to major knowledge providers in the interfirm knowledge network (i.e., it has high eigenvector centrality), the external knowledge that this firm acquires will be mainly limited to mature knowledge. However, such knowledge can inhibit search for innovation and reduce NPD performance, because mature knowledge is well-established and often less valuable for recombinant efforts that aim to identify new technological opportunities (Christensen, 1997).

Moreover, accessing mature knowledge can also inhibit effective search process due to the detrimental effects of the dominant logic embedded in such knowledge. Dominant logic — a set of general principles (Prahalad and Bettis, 1986) — can lead to uncontrolled consequences by generating core rigidities or competency traps (Leonard-Barton, 1992; Levitt and March, 1988). Core rigidities are the core capabilities of the past that now may be out of date and hinder innovation, because the technical experience that facilitated the innovativeness of mature knowledge in previous NPD projects may be inappropriate in current projects (Prahalad and Hamel, 1990). If a focal firm with high eigenvector centrality mainly acquires knowledge from other firms that are central in an interfirm knowledge network, the external knowledge searched by this firm would be less useful for generating new products, reducing NPD performance. This is stated in the following hypothesis.

H3. A firm's eigenvector centrality in an interfirm knowledge network has a negative effect on its subsequent NPD performance.

3. Methodology

3.1. Data

We select the U.S. pharmaceutical industry (SIC code: 2834) as the empirical setting for four reasons. First, the U.S. pharmaceutical industry is a knowledge-intensive sector, where innovation plays a critical role in building and sustaining competitive advantages. This industry has also been used to study innovation in many other studies (e.g., Dong and Yang, 2015; Hoang and Rothaermel, 2005; Xu, 2015; Yang and Shyu, 2009), indicating the appropriateness of this choice and enabling comparisons with the literature. Second, pharmaceutical firms not only rely on internally generated knowledge, but also develop new products by extensively leveraging external knowledge (Dong and Yang, 2015; Hoang and Rothaermel, 2005; Xu, 2015). Third, archival data for new products are available for the U.S. pharmaceutical firms due to the regulations governing this sector, allowing us to measure NPD performance in an objective and reliable manner. Finally, focusing on a single industry can control for unobservable confounding factors related to industry heterogeneity.

To better test the causal relationships underlying our hypotheses, we use a longitudinal design and construct a panel data set from three independent archival sources. First, we collected financial data for the U.S. public firms with SIC code 2834 from the Standard and Poor's Compustat database. Second, we obtained patent citations data for all U.S. utility patents granted from 1976 to 2006 from the National Bureau of Economic Research's (NBER) Patent Citations database (Hall et al., 2001). We aggregated patent-level citations to the firm level by counting the number of each cross-citation pair (as the weight of knowledge tie) in each year, constructed interfirm knowledge networks based on cross-citation pairs for each year, and then calculated knowledge network centrality for each firm-year observation. Patent citations data were then merged to financial data by firm GVKEY. Finally, we collected new drug approval data from the U.S. Food and Drug Administration (FDA) from 2003 to 2010 to measure NPD performance, and merged them to other data using company names. Since the new drug approval data are available since 2003, our panel structure starts in this year. As explained later, we need to have a five-year rolling window to capture NPD performance in the subsequent period, allowing the end year as 2005 (i.e., 2010–5 = 2005). This resulted in a final sample of 153 unique firms in 2003 to 2005, with a total number of 294 firm-year observations.

3.2. Knowledge network centrality

Since our data have a firm-year panel structure, we use a complete network approach to construct interfirm knowledge networks based on all the patent citation pairs made by the U.S. pharmaceutical firms — which are either public in our final sample, or are private and not included in our final sample — in each year. Fig. 1 shows an example of the interfirm knowledge network of the U.S. pharmaceutical industry in 2005. Patent citation pairs can indicate knowledge flows and ties among firms (Dong and Yang, 2015; Wang et al., 2016). As mentioned earlier, the number of the same patent citation pairs was used as the weight to indicate the importance of each knowledge tie when calculating knowledge network centrality.

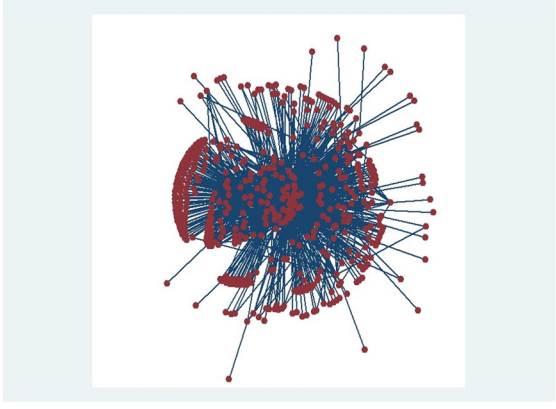

Fig. 1. Interfirm Knowledge Network in 2005.

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Our calculation of knowledge network centrality followed widely used, standard approaches. Stata 12.1 was used for the network analysis, and we applied the command "netsis" to calculate all the centrality measures (Miura, 2012), which is a publicly available program with embedded algorithms to automatically generate degree, closeness, eigenvector and betweenness centrality based on network data.

Specifically, degree centrality was calculated by the number of knowledge ties that a focal firm i had in a specific year t, shown by the following formula (Freeman, 1979; Miura, 2012).

$$Degree_{it} = \frac{No.\ of\ ties_{it}}{No.\ of\ firms_t} \tag{1}$$

Closeness centrality was calculated by the inverse of the average shortest distance of knowledge ties between a focal firm i and all other firms in a specific year t, shown by the following formula (Freeman, 1979; Miura, 2012).

$$Closeness_{it} = \frac{No.\ of\ firms_t - 1}{\sum No.\ of\ ties\ as\ shortest\ distance_{it}} \tag{2}$$

Eigenvector centrality was calculated in the following steps (Bonacich, 1972; Miura, 2012). Let $A = a_{ij}$ be the adjacency matrix of interfirm knowledge network (value = 1 if there is a knowledge tie among two firms, value = 0 otherwise) in a specific year t, x_i denote the score of the ith firm in a row of the adjacency matrix, x_j denote the score of the jth firm in a column of the adjacency matrix, and γ be the principle eigenvector which maximizes the eigenvalue, and thus we have:

$$x_{it} = \frac{1}{\gamma}\sum a_{ijt}x_{jt} \tag{3}$$

In vector notation, Eq. (3) can be rewritten as follows.

$$AX = \gamma X \tag{4}$$

Finally, eigenvector centrality is the greatest eigenvector solution γ with nonnegative entries (Cvetkovic et al., 1995), as follows.

$$Eigenvector_{it} = \max(\gamma) \tag{5}$$

3.3. NPD performance

In this study we follow the prior literature and use a count measure of the number of new drugs approved by the FDA to capture NPD performance (Xu, 2015). To avoid reverse causality — superior NPD performance may lead to a central position in an interfirm knowledge network rather than the causal relationship that we hypothesize — we measure NPD performance in the future five years. After pharmaceutical firms obtained patents by which time we can observe the citations made in these patents, they needed to conduct clinical trials to prove the safety of the new drug before the FDA approves it. The duration of this process varies across firms and may take up to five years, and thus we use a five-year rolling window to calculate NPD performance.[3] Specifically, we count a firm's cumulative number of new drugs approved by the FDA over a five-year rolling window.[4] A five-year rolling window has been widely used in the prior literature when measuring innovation (Fleming et al., 2007; Wang et al., 2014).

3.4. Control variables

To rule out possible confounds, we control several factors in the empirical analysis. First, we control *betweenness centrality* as another type of network centrality that has been used in the literature, as betweenness centrality in interfirm collaboration networks has been found to impact innovation (Gilsing et al., 2008). In an interfirm knowledge network, betweenness centrality was calculated by the number of times that a focal firm i was on the shortest path between a pair of other firms (indicated by m and n) in a specific year t (Freeman, 1979; Miura, 2012), as follows.

$$Betweenness_{it} = \sum \frac{No.\ of\ shortest\ paths\ \ of\ m\ and\ n\ via\ i_{it}}{No.\ of\ shortest\ paths\ of\ m\ and\ n_t} \Big/ \frac{1}{2}(No.\ of\ firms_t - 1) \times (No.\ of\ firms_t - 2) \tag{6}$$

Second, *R&D intensity* could influence NPD performance (Cohen and Levinthal, 1990), which is controlled by R&D spending over total sales. Third, *firm size* may also affect NPD performance, as large firms with more slack may fund more NPD projects (Nohria and Gulati, 1996), whereas small firms may be more flexible and innovative (Christensen, 1997). We control firm size by a proxy as the natural logarithm of total sales (Dong, 2016; Dong and Yang, 2015). Finally, time period may influence firm innovativeness, and so we include *year dummies* in our analysis. Table 1 reports the descriptive statistics, while Table 2 reports the correlations among our variables.

4. Results

To test our hypotheses, we estimate the following regression model for firm i in year t, where ε indicates the residuals.

$$NPD_{it} = \beta_0 + \beta_1 Degree_{it} + \beta_2 Closeness_{it} + \beta_3 Eigenvector_{it} + \beta_4 Betweenness_{it} + \beta_5 R\&D_{it} + \beta_6 Size_{it} + \beta_7 YearDummy2004 + \beta_8 YearDummy2005 + \varepsilon_{it} \tag{7}$$

Since our dependent variable NPD performance is a count variable, Poisson or negative binomial regression is suitable for estimation (Greene, 2003), and we use both approaches to examine the sensitivity of the results to model specifications. Additionally, some firm-year observations had zero new drugs in NPD performance. We thus estimate another Tobit regression with left-censoring to further check the robustness of the results (Greene, 2003). As our panel data set includes repeated measures from the same firm, clustered robust standard errors are used in all analysis.

Table 3 shows the regression results. For each regression analysis we use a stepwise procedure to first estimate a control model, and then add centrality variables into the model. In Table 3, columns (1) and (2) present the results for Poisson regression, columns (3) and (4) show the results for negative binomial regression, and columns (5) and (6) provide the results for Tobit regression. Qualitatively similar results were found across all these model specifications, indicating the robustness of our results.

We found that degree centrality had a statistically significant and *positive* effect on NPD performance. Thus, H1 was supported. In

[3] While new drug development may take more than ten years in total, it is important to note that we use backward patent citations to capture the knowledge inputs used in developing new patented knowledge that is related to new drugs. In other words, by the time when the citations were made by a firm in its patents, it was not at the beginning of NPD process but new knowledge for drug development had already been invented and patented. Backward citations reflect the knowledge inputs that had been searched by the firm since the beginning of new drug development. Thus, from the time when new patented knowledge is invented and its citations have been made, to the time when the FDA approves a new drug, the firm only needs to conduct clinical trials, which may take five years at the most.

[4] We count new drugs approved in 2004–2008 for the observations in 2003, count new drugs approved in 2005–2009 for the observations in 2004, and count new drugs approved in 2006–2010 for the observations in 2005.

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Table 1
Descriptive statistics.

	Mean	SD	Min	Max
NPD performance	1.286	2.678	0	19
Degree centrality	0.309	0.908	0.002	8.171
Closeness centrality	1.934	28.386	0.076	487
Eigenvector centrality	0.016	0.076	0.000	0.675
Betweenness centrality	0.020	0.043	0	0.329
R&D expenditure (in M$)	651.472	1643.890	0.203	12,183
Sales (in M$)	3963.687	9831.305	0.062	52,516

addition, we found that closeness centrality had a statistically significant and *negative* effect on NPD performance. Thus, H2 was also supported. Finally, eigenvector centrality also had a statistically significant and *negative* effect on NPD performance, supporting H3. Therefore, all our hypotheses were supported by the empirical results. Consistent with H1, we find that a firm's degree centrality in an interfirm knowledge network is positively related to its NPD performance in the subsequent five-year period. Interestingly, we find empirical support for H2 and H3, suggesting the negative impacts of closeness centrality and eigenvector centrality on NPD performance. Consistent with our arguments for H2, a firm's closeness centrality in an interfirm knowledge network is negatively associated with its subsequent NPD performance. The empirical results also corroborate our arguments for H3, as firms with higher eigenvector centrality in an interfirm knowledge network have better NPD performance than those with lower eigenvector centrality.

5. Discussion and implications

5.1. Theoretical implications

Our study enriches the innovation literature in three ways. First, we shift the attention from interfirm collaboration networks to interfirm knowledge networks when studying the role of network centrality in innovation. While interfirm collaboration networks require formal partnerships, an interfirm knowledge network consists of knowledge flows among firms that are often invisible (Dong and Yang, 2015). Although such interfirm knowledge networks are difficult to observe, patent citations reflect how knowledge flows among firms in an industry, and are particularly salient in knowledge-intensive industries such as pharmaceuticals. We find that firms' structural positions in their interfirm knowledge network play an important role in facilitating or inhibiting their innovation activity.

Second, we examine and compare the impacts of different measures for knowledge network centrality on NPD performance. We deepen our understanding of knowledge network centrality by distinguishing different centrality measures and their impacts on innovation. We explain that these centrality measures indicate central positions from different perspectives, and thereby influence NPD performance in distinct ways. In an interfirm knowledge network, different types of centrality are not always good for developing new products; degree centrality is positively related to NPD performance whereas closeness centrality and eigenvector centrality are negatively related to NPD performance. While it is good to focus on the knowledge flows directly used for innovation, exposure to abundant knowledge from other firms in the network and acquisition of mature knowledge from those that are central in the network are associated with lower NPD performance. As such, this study contributes a new understanding of the dark side of knowledge network centrality. To the best of our knowledge, no prior studies have has explored the role of knowledge network centrality in innovation and highlighted how it can be a double-edged sword for new product development.

Finally, we collect a panel data set from multiple, objective data sources and provide empirical evidence corroborating our hypotheses. In particular, we dynamically construct interfirm knowledge networks for the U.S. pharmaceutical industry over time. Our results show the counter-intuitive findings that closeness centrality and eigenvector centrality in an interfirm knowledge network reduce NPD performance, underlining the danger of oversimplifying the complex impacts of knowledge network centrality on innovation.

Table 2
Correlations.

	(1)	(2)	(3)	(4)	(5)	(6)
(1) NPD performance						
(2) Degree centrality	**0.300**					
(3) Closeness centrality	−0.028	−0.020				
(4) Eigenvector centrality	0.148	**0.956**	−0.012			
(5) Betweenness centrality	**0.369**	**0.929**	−0.026	**0.852**		
(6) R&D	−0.076	−0.070	−0.014	−0.047	−0.086	
(7) Size	**0.553**	**0.460**	−0.016	**0.329**	**0.555**	**−0.313**

Note: Correlations in bold are significant with $p < 0.05$.

5.2. Managerial implications

This study provides important implications for managers. We find that a central position in an interfirm knowledge network is a double-edged sword for innovation. On the one hand, a locally central position is good for developing new products through focused problemistic search. On the other hand, a globally central position does more harm than good by encouraging firms to lose focus in the search process. In particular, a central position with close knowledge ties to all other firms in the industry may induce information overload, and hinder efficient search for innovation. Moreover, a central position linking to other central firms mainly allows the acquisition of mature knowledge and reduces the likelihood of successfully recombining knowledge into new inventions. Therefore, oversimplifying the meaning of and the complex innovation impacts of centrality in an interfirm knowledge network can lead to undesirable innovation strategies and outcomes. To encourage innovation, managers, and especially those in the U.S. pharmaceutical firms, need to build a locally central but globally distant position in their interfirm knowledge network, and keep away from other firms that are central in the network.

5.3. Limitations and future research

Like other empirical work, our study has some limitations. First, we focus on interfirm knowledge networks in this study, and the knowledge flows between firms and universities or government institutes are not taken into account. Future research may thus want to incorporate other types of organizations to construct more holistic interfirm knowledge networks. Second, we focus on knowledge network centrality in this study, as network centrality is one of the most important structural properties of a network. In particular, we empirically examine the impacts of degree, closeness centrality and eigenvector centrality in an interfirm knowledge network on NPD performance. Future studies could reconceptualize the meaning of betweenness centrality in the context of an interfirm knowledge network and consider other structural properties of the network that may affect innovation. Third, we examine the impacts of different measures for knowledge network centrality on the overall NPD performance without distinguishing the types of innovation. While our explanations are not specific to incremental or radical innovation, the empirical setting of the U.S. pharmaceutical industry seems regulated by only allowing really innovative new drugs to be approved by the FDA. In this sense, our findings are more applicable to radical innovation compared to incremental innovation.[5] Last but not least, we collect data from public firms in the U.S. pharmaceutical industry,

[5] We thank one anonymous reviewer who suggested this point.

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Table 3
Regression results.

	Poisson model		Negative binomial model		Tobit model	
	(1)	(2)	(3)	(4)	(5)	(6)
Degree centrality		0.677**		0.721*		3.311**
		(0.341)		(0.282)		(1.324)
Closeness centrality		−0.011***		−0.013***		−0.022***
		(0.003)		(0.003)		(0.005)
Eigenvector centrality		−8.834**		−8.386**		−37.625***
		(4.112)		(2.885)		(14.300)
Betweenness centrality		−1.017		−0.462		1.010
		(3.818)		(4.665)		(16.214)
R&D	0.008**	0.007**	0.009	0.007	0.021	0.016
	(0.003)	(0.003)	(0.006)	(0.005)	(0.013)	(0.012)
Size	0.406***	0.370***	0.363***	0.319***	1.005***	0.797***
	(0.056)	(0.068)	(0.051)	(0.065)	(0.219)	(0.215)
Year 2004	−0.020	0.032	−0.073	−0.015	−0.146	0.068
	(0.097)	(0.115)	(0.136)	(0.141)	(0.390)	(0.387)
Year 2005	−0.002	−0.048	−0.006	−0.013	0.106	0.065
	(0.106)	(0.121)	(0.127)	(0.130)	(0.395)	(0.382)
Constant	−2.454***	−2.307***	−2.155***	−2.019***	−6.078***	−5.358***
	(0.434)	(0.455)	(0.386)	(0.401)	(1.510)	(1.423)
Wald Chi-square/F	57.940***	134.400***	54.280***	114.410***	5.530***	5.850***

Note: $n = 294$. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Clustered robust standard errors are in parentheses. Dependent variable is NPD performance in the future five years.

which are often large and well established, and caution should taken when generalizing our findings to other types of firms or other industries. Future studies may thus collect data from private firms in other industries to examine our findings.

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Appendix A. Supplementary information

In addition to the information presented in the methodology of this paper, we compile the data for interfirm knowledge networks of the U.S. pharmaceutical industry from 1976 to 2006 into the PharmaNet database. This database contains a total of 19,045 dyad-year observations and 4061 firm-year observations with a number of variables about firm identifiers, network properties, as well as geographic and financial information (Dong and Yang, 2016). The database and a user guide are freely available on https://sites.google.com/a/rug.nl/pharmanet.

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