ERIC (ER) FANG, JONGKUK LEE, ROBERT PALMATIER, and SHUNPING HAN*

Launching breakthrough and incremental new products is vital to firm performance; it also resonates with both ego (i.e., directly connected partners) and global (i.e., interconnected ties in an industry) network perspectives. Prior research has listed several ego network– and global network–level factors that affect innovations, but this study goes a step further, to reveal the interactions of these factors as critical product launch mechanisms. An analysis of alliance networks in the consumer packaged goods industry from 1990 to 2010 shows that a central position in a global network represents a double-edged sword: it improves a firm's incremental new product launches but harms its breakthrough new product launches. Furthermore, a firm's ego network (manifested as density and diversity) and R&D capability enable it to leverage its global network position by enhancing the benefits for incremental new products and mitigating its hazards for breakthrough new products. This study's findings thus offer new insights into the role of ego and global networks in facilitating or hindering new product launches.

Keywords: ego network density, ego network diversity, global network centrality, incremental new products, breakthrough new products

Online Supplement: http://dx.doi.org/10.1509/jmr.13.0226

If It Takes a Village to Foster Innovation, Success Depends on the Neighbors: The Effects of Global and Ego Networks on New Product Launches

Alliances among firms and institutions are prevalent in the consumer packaged goods (CPG) industry; forming alliances is a strategy by which companies can improve the performance of new product innovations. For example, in response to the challenges of internal development of new products, reduced innovation rates, and higher R&D costs in the late 1990s, Procter & Gamble (P&G) initiated its "Connect + Develop" program, a new innovation strategy to connect with external sources of ideas and develop those ideas into profitable products (Dodgson, Gann, and Salter 2006). From 2000 to 2009, approximately 3,000 R&D interfirm collaborations occurred in the CPG industry. However, we know little about their actual consequences for innovation or the types of new products that resulted.

Breakthrough new products incorporate substantially new features that provide novel, significant consumer benefits; incremental new products involve relatively marginal improvements to existing products (Chandy and Tellis 1998; Sorescu and Spanjol 2008). Breakthrough new products provide new growth opportunities, as well as a high risk of failure. By reinforcing the firm's current capabilities, incremental new products instead provide stable cash flows, although with

*Eric (Er) Fang is Associate Professor of Marketing and James F. Towey Faculty Fellow, University of Illinois at Urbana-Champaign (e-mail: erfang@illinois.edu). Jongkuk Lee (corresponding author) is Associate Professor of Marketing, Ewha School of Business, Ewha Womans University (e-mail: jongkuk@ewha.ac.kr). Robert Palmatier is John C. Narver Endowed Chair in Business Administration and Professor of Marketing, Foster School of Business, University of Washington (e-mail: palmatrw@uw.edu). Shunping Han (corresponding author) is Professor of Marketing, College of Business, Nanjing University (e-mail: shunping@nju.edu.cn). The first author acknowledges the financial support of the National Science Foundation of China (grant no. 71328203), and the fourth author acknowledges the financial support of the National Natural Science Foundation of China (grant no. 71272098).

ISSN: 0022-2437 (print)
1547-7193 (electronic)

Journal of Marketing Research
Vol. LIII (June 2016), 319–337
DOI: 10.1509/jmr.13.0226

limited potential for further firm growth or value (Sorescu and Spanjol 2008). This trade-off between risk and return suggests that firms must constantly balance their breakthrough and incremental new product efforts. To do so, they often turn to alliance networks, which represent viable external sources of innovation (Mallapragada, Grewal, and Lilien 2012). Collaborations enable firms to tap alliance networks and access information to drive their new product development (Ahuja 2000; Wuyts, Dutta, and Stremersch 2004). However, no studies have examined how alliance networks might differentially drive breakthrough and incremental new products.

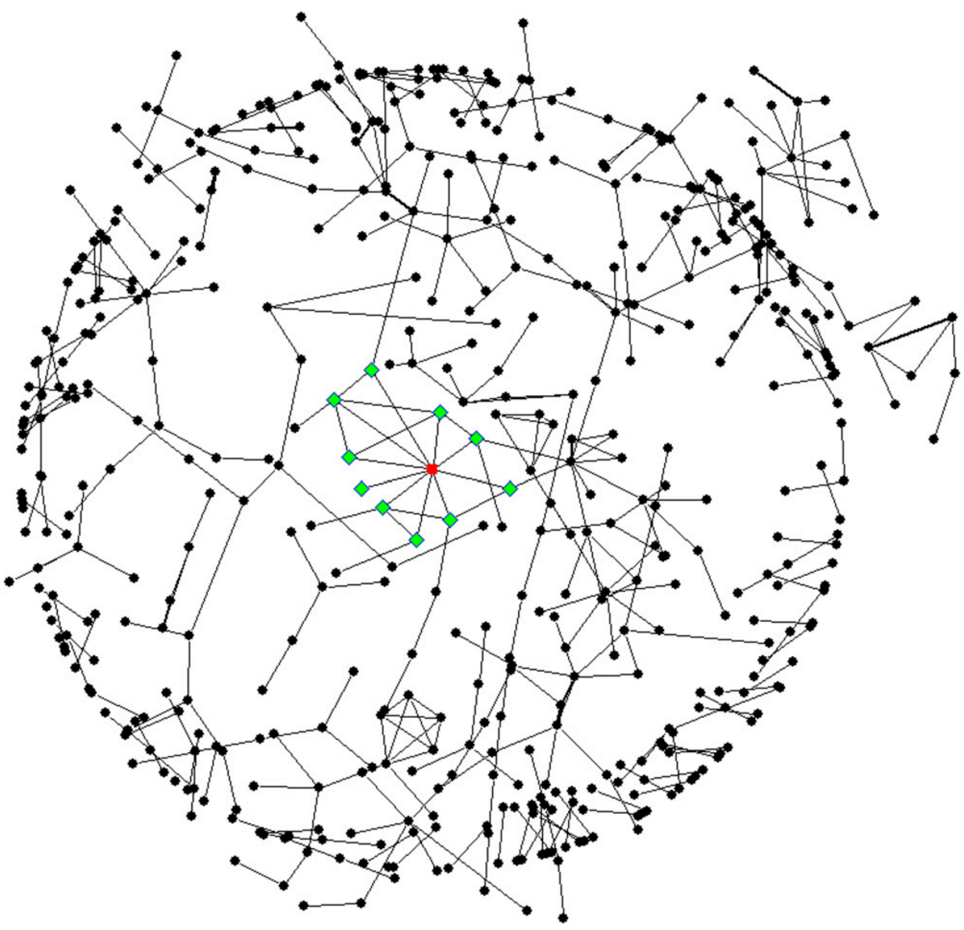
Furthermore, according to an ego network perspective, a firm's innovations stem from collaborations with directly connected partners who pursue joint value creation, such as by pooling their complementary resources and promoting effective cooperation (Jap 1999). But a global network perspective instead posits that a firm can move beyond direct connections to gain other benefits, such as information from knowledge diffusion across a broader social space, depending on the overall structure of ties in an industry (Schilling and Phelps 2007). We posit that by pooling resources with directly connected partners, a firm can accumulate a relevant base of knowledge that makes its access to and use of resources in different parts of the global network more effective. That is, even as the firm accesses industry-wide information and resources through its position in a global network, its directly connected partners can help it filter out irrelevant information, interpret new information, and integrate that information with existing practices. As an example, Figure 1 displays P&G's alliance network in 1995: its position in the overall CPG industry and its ego network, which included public firms such as Abbott, private firms such as Cephalon, and nonprofit organizations such as University of Florida. Through this ego network, P&G was able to tap the entire CPG industry to find relevant information.

Considering the potentially divergent outcomes of such connections, we seek answers to three important research questions:

- RQ_1: How does a firm's position in a global network affect its breakthrough and incremental new product launches?
- RQ_2: How does a firm's ego network interact with its position in the global network to facilitate or hinder new product launches?
- RQ_3: Does a firm's R&D capability moderate the effect of a firm's position in a global network on its new product launches, considering its evident importance for product launches (Griliches 1984)?

Figure 1

GLOBAL NETWORK IN THE CPG INDUSTRY AND EGO NETWORK OF P&G IN 1995



Notes: The square in the center refers to P&G, and the diamonds refer to P&G's ego network partners in 1995.

To address these questions, we used a unique data set pertaining to the CPG industry during 1990–2010 that we compiled from multiple sources (e.g., SDC Joint Ventures and Alliances, ProductScan, Compustat). In our estimation approach, we adopt a system generalized method of moments (GMM) to account for the dynamic panel nature of our data, along with instrumental variables to address potential endogeneity issues in network-partner selections. From these analyses, we determine that a firm's central position in a global network enhances its incremental new product launches but harms its breakthrough new product launches; a sparsely connected, diverse ego network minimizes both these impacts. Furthermore, a firm's R&D capability helps it leverage a central position in its global network to foster more incremental new product launches.

These findings generate three main contributions to alliance and new product literature. First, whereas prior research has examined alliance networks at various levels (see Table 1), we seek to explicate alliance networks by revealing interactions across levels. The effect of the firm's position in the global network is contingent on ego network factors, which determine the firm's capacity to absorb resources and capabilities from the broader social space. Therefore, focusing on either the global or the ego network, but ignoring their nuanced interactions, creates a biased picture of the link between alliance networks and new product launches.

Second, we differentiate the effects of the alliance network on breakthrough versus incremental new products, rather than broadly considering innovations and new product development in general (Mallapragada, Grewal, and Lilien 2012; Owen-Smith and Powell 2004; Tsai 2001). With this distinction, we can specify dual effects of a central position in the global network: positive for incremental new products and negative for breakthrough ones. We also identify moderating influences of the firm's ego network and R&D capability on the effects of its global network position on incremental and breakthrough new product launches.

Finally, we sought to apply our results to scenarios with higher and lower values of betweenness centrality, ego network density, ego network diversity, and R&D capability to answer a managerially critical question: How should firms structure their ego and global networks to optimize their breakthrough and incremental new product launches, and when does it depend on their R&D capabilities? For example, for breakthrough new product launches, the optimal strategy features low global network betweenness centrality and ego network density but high ego network diversity independent of R&D capabilities. This strategy, which we refer to as a "breakthrough new product–driving network strategy," generated 26% more breakthrough new products than the baseline condition. Alternatively, for incremental new product launches, the optimal strategy is to occupy a central position in the industry network, with high ego network density but low ego network diversity. The increase in incremental new products in this case was 18% for firms with high R&D capability and 13% for firms with low R&D capability, compared with the baseline condition. Accordingly, our study offers new insights into the unique determinants of new product launches.

ROLE OF INTERFIRM NETWORKS IN NEW PRODUCT LAUNCHES

Breakthrough and Incremental New Product Launches

In the CPG industry, products that supply meaningful consumer benefits are critical to success. We argue in this study that breakthrough innovations are not limited to just technological advances (Chandy and Tellis 1998). We define breakthrough new products as those that are the first to provide novel and significant benefits to consumers, whereas incremental new products do not provide novel or significant consumer benefits compared with existing products (Sorescu and Spanjol 2008). Breakthroughs create value in the market, whether because they improve product features, packaging, or formulations (e.g., Lysol No-Touch Hand Soap System automatically dispenses just the right amount of soap) or create new markets (e.g., Huggies Pull-Ups created a new disposable underwear category for children). Technological breakthroughs are critical types of innovation that deviate from current technological trajectories in technology-intensive industries (Subramaniam and Youndt 2005; Wuyts, Dutta, and Stremersch 2004), but breakthroughs in CPG industries instead tend to feature product developments that improve consumer benefits by moving the product beyond a current market trajectory. In contrast, incremental new products refine existing versions (e.g., minor changes to packages, quality improvements, line extensions to add a new flavor), make relatively small changes, and reinforce existing market trajectories (Ettlie 1983).

In addition, breakthrough and incremental new products differ in the knowledge acquisition and assimilation processes they induce. In terms of knowledge acquisition, launches of breakthrough new products require the firm to gain novel information or capabilities that deviate from its current knowledge. To launch incremental new products, firms instead need to gather information that aligns with their current knowledge (Subramaniam and Youndt 2005). In addition, breakthrough new products require more extensive, novel knowledge integration because the firm seeks to offer new, innovative solutions with significant potential to enhance consumer benefits in the market (Sorescu and Spanjol 2008). Incremental new products instead demand efficiency in knowledge integration so that the firm can combine existing technological or market trends and update its products in a timely manner (Lee 2011).

Both knowledge acquisition and knowledge integration, and thus new product capabilities, depend on a firm's ability to accumulate a relevant base of knowledge (Narasimhan, Rajiv, and Dutta 2006). If it collaborates with partners, a firm extends its knowledge base beyond its organizational boundaries and can exploit an alliance network (Wuyts, Dutta, and Stremersch 2004). In such knowledge-based networks, the firm gains access to different partners' knowledge and then leverages that knowledge in its new product efforts (Phelps, Heidl, and Wadhwa 2012).

Global and Ego Networks

We consider the influence of global and ego networks on innovation. A global network that comprises interfirm linkages within an industry becomes a source of industry-wide information, so the position in the global network should facilitate or hinder the acquisition of knowledge in

Table 1
SELECTED LITERATURE ON THE EFFECTS OF GLOBAL AND EGO NETWORK ON NEW PRODUCT LAUNCHES

			Research Scope				
Study	*Context*	*Network Properties*	*Ego Network*	*Global Network*	*Distinction Between Breakthrough and Incremental Innovations*	*Empirical Correction of Endogeneity*	*Findings*
Baum, Calabrese, and Silverman (2000)	511 Canadian biotech firms	Diversity of information and capability per alliance	√				Network size and efficiency of a startup at the time of its founding enhance innovation performance.
Fang (2008)	143 customer-component manufacturer alliances	Network connectivity	√				Customer participation has differential effects on innovativeness and speed, depending on customer network connectivity.
Mallapragada, Grewal, and Lilien (2012)	817 open-source projects	Degree, betweenness and closeness centrality	√	√			A central position of founders in the developer user community can reduce time to product release.
Nerkar and Paruchuri (2005)	R&D networks in DuPont	Centrality, structural holes	√	√			Individual position in an intraorganizational network of inventors predicts the likelihood of knowledge being selected by other inventors.
Obstfeld (2005)	152 individuals in the engineering department of an automotive manufacturer	Structural holes	√				A tertius iungens orientation, dense social networks, and diverse social knowledge predict involvement in innovation.
Owen-Smith and Powell (2004)	482 dedicated biotechnology firms	Betweenness centrality		√			Network centrality in a geographically dispersed network positively affects innovation.
Tsai (2001)	60 business units of manufacturing companies	Betweenness centrality		√			Network centrality is positively related to innovation; however, the benefits depend on the firm's absorptive capacity.
Van Beers and Zand (2014)	12,811 innovating firms	Functional and geographical diversity	√		√		Functional diversity leads to novel products, whereas geographical diversity results in successful adaption of existing products.
Wuyts, Dutta, and Stremersch (2004)	58 pharmaceutical firms	Technological diversity	√		√		Technological diversity in a firm's ego network has a positive effect on both radical and incremental new products.
This study	91 firms in the CPG industry	Betweenness and closeness centrality, network connectivity and diversity	√	√	√	√	A central position in the industry has differential effects on breakthrough and incremental new product launches, and the effects are contingent on ego network connectivity and diversity.

an industry. In particular, network centrality, or the extent to which an actor is central to a network (Monge and Contractor 2003), reflects a firm's position in an industry, which defines its access to external information and resources. We focus on two common aspects: closeness and betweenness centrality. In a global network, closeness centrality pertains to the distance feature, equivalent to the efficiency of its access to other firms by short paths, whereas betweenness centrality reflects a mediation aspect, or the extent to which the firm can mediate flows of information in a global network (Mallapragada, Grewal, and Lilien 2012). Such flows of information can take place on any paths that connect firms in a global network, rather than being restricted to the shortest paths (Freeman, Borgatti, and White 1991; Stephenson and Zelen 1989). Although a firm's position in the global network determines the potential amount of information and resources it can access, directly or indirectly, the outcomes of a global network also depend on the firm's ability to transfer external resources to itself and transform them into new products (Tsai 2001).

We propose that ego network density and diversity might facilitate or hinder this absorption of resources from a global network. Ego network density is the degree to which ego network partners connect with one another (Coleman 1990), and ego network diversity is the amount of variation in the types of ego network partners (Lavie and Miller 2008; Van Beers and Zand 2014).

On the one hand, ego network density should help coordinate the effective absorption of resources from a global network of both direct and indirect partners. Highly interconnected partners in a firm's ego network interact frequently and can leverage knowledge spillovers; they facilitate exchange-inducing norms and sanction opportunistic behaviors (Obstfeld 2005). By reducing the uncertainty surrounding an exchange, a firm's interconnected ego network motivates partners to commit and cooperate. As such, the ego network itself represents a form of coordination that facilitates robust, collective actions among directly connected partners (Kogut 2000). However, prior research also notes that highly interconnected ego networks can constrain the types of information and resources the firm accesses, such that they act as barriers to innovations, particularly those that go beyond the current market or technological practices (Moran 2005; Rowley, Behrens, and Krackhardt 2000).

On the other hand, diverse ego network partners might affect the assimilation of industry-wide information gained from a global network. Prior research has noted increasing learning opportunities from more diverse partners, such as when a firm applies information and resources from one alliance to others, which generates a synergistic effect of partner diversity (Swaminathan and Moorman 2009; Wuyts, Dutta, and Stremersch 2004). By pooling resources with diverse partners in an ego network, the firm gains more options and flexibility in applying industry-wide information from the global network in novel ways. However, having diverse ego network partners also might increase coordination complexity (Cui and O'Connor 2012) and thus constrain the efficiency with which the firm can transform knowledge from the global network into innovations.

These distinct, complementary roles of global and ego network properties suggest that they are two essential elements that interact to determine new product innovations. For example, a firm might exhibit high network centrality in the global network but low density in its ego network if it has partners that are located in different parts of the industry and isolated from one another. Another firm might achieve the opposite position by targeting a particular peripheral domain to solicit partners that are well connected to one another (high density in the ego network) but not connected to other parts of the industry (low centrality in the global network).

R&D capability, which refers to a firm's ability to develop technology competencies and processes to transform innovative ideas into new products (Dutta, Narasimhan, and Rajiv 1999), has long been recognized as a critical source of absorptive capacity for more effective interorganizational learning. As such, in addition to ego network, R&D capability can also facilitate a firm to recognize and synthesize external resources prevailing in the global network (Xiong and Bharadwaj 2011).

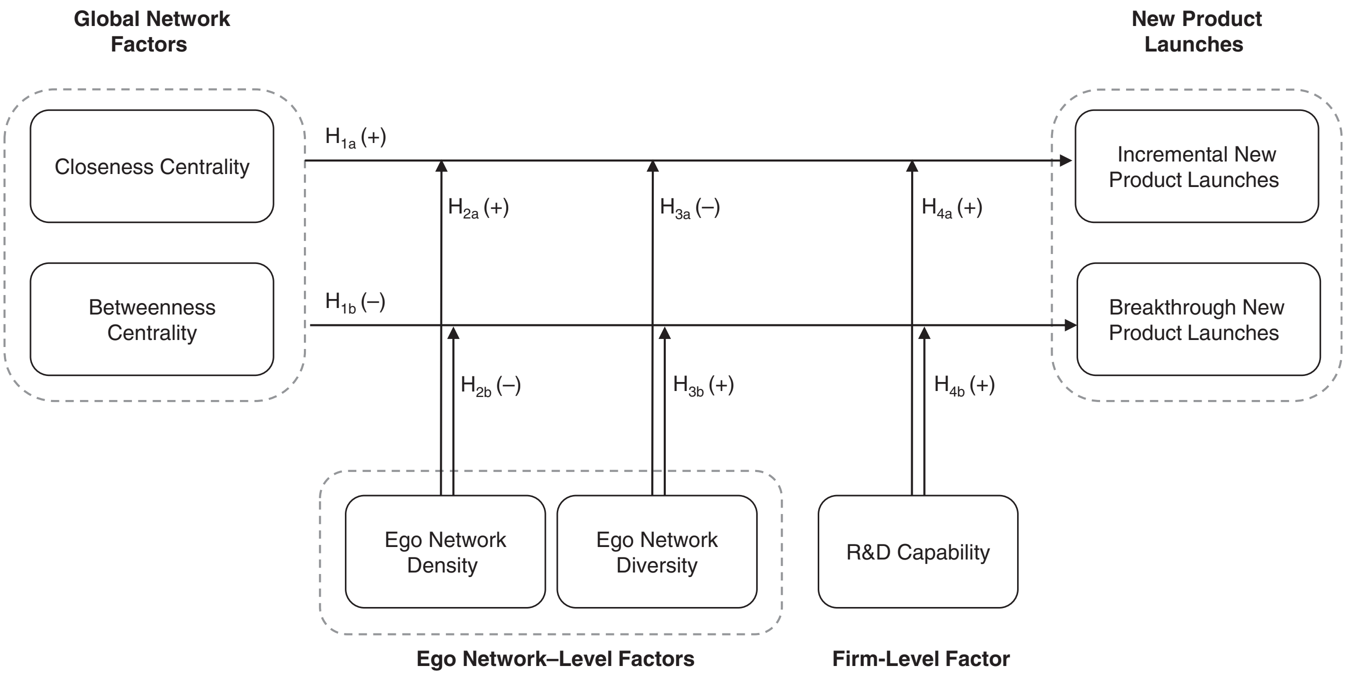
CONCEPTUAL MODEL AND HYPOTHESES

We argue that a firm's position in the global network exerts differential effects on its launches of incremental and breakthrough new products and that its ego network and R&D capability moderate these effects. Figure 2 illustrates our conceptual model.

Effects of the Global Network on Breakthrough and Incremental New Product Launches

Closeness and betweenness centrality in the global network allow firms to capture more knowledge from spillovers from other organizations in the industry. With greater closeness centrality, a firm can access industry knowledge more efficiently and at a lower cost because its location near other firms in the network allows it to receive and spread information more quickly. As Freeman (1979, p. 225) notes, closeness "means fewer message transmissions, shorter times, and lower costs." In addition, when located closer to other firms in a development network, a firm can obtain information with fewer intermediary steps, which reduces the chances of information distortion during transmission. Similarly, when a firm is a "critical intermediary" among others, or "in the middle of things" (Van den Bulte and Wuyts 2007, p. 21), a high betweenness centrality means the firm has access to more information flows in the network and can control that information better (Brass, Butterfield, and Skaggs 1998; Freeman 1979). A firm located between other firms functions as an information gatekeeper (Ahuja, Galletta, and Carley 2003). Thus, both closeness and betweenness centrality facilitate access to industry-specific information and should enhance a firm's incremental new product launches because the firm can use the spilled-over industry-specific information to refine its existing products according to the dominant technological or market trajectory. For example, since the late 1990s, Clorox, which could access industry-wide information more promptly than its competitors through its direct and indirect partners in the CPG industry, has identified various new opportunities and tracked industry practices to introduce incrementally improved new products, with both cost reductions and performance improvements (Calvey 2012).

Figure 2
THE EFFECTS OF INDUSTRY AND EGO NETWORK FACTORS ON NEW PRODUCT LAUNCHES



In contrast, a central position in the global network can hinder launches of breakthrough new products. Being deeply engaged in an industry-specific context could bias firms against competency-destroying, noncumulative innovations because the firms can rely on path-dependent routines and strategies (Teece 2007). Closeness centrality often hinders a firm's ability to view new things broadly or explore ideas from outside the industry (Grabher 1993). Similarly, betweenness centrality can lock a firm in to industrial contexts by embedding it in the global network, made up of paths among other participants (Mallapragada, Grewal, and Lilien 2012). Han, Kim, and Kim (2001) show that in food industries, incumbents better protected from the threats of outside industries tend to be less innovative and to focus more on incremental changes. This effect is greater to the degree the firm is embedded in the industrial context through its position in the network. Thus, a central position in the global network likely undermines a firm's ability to think outside the box and willingness to cannibalize its sales of existing products, both of which are important factors for innovating breakthrough new products (Chandy and Tellis 1998).

However, we also recognize the possibility that betweenness centrality provides a good brokerage position for accessing more novel information and thus cultivates breakthrough innovations. Although betweenness centrality can have contrasting effects on breakthrough innovations, access to novel information through a brokerage position should be minimized in an industry-specific network. Therefore, betweenness centrality, along with closeness centrality, in an industry-specific global network should act as a constraint on rather than facilitator of breakthrough new product launches.

H_1: Betweenness and closeness centrality (a) enhance incremental new product launches but (b) hinder breakthrough new product launches.

Moderating Effects of Ego Networks

Ego network density. Although a central position provides more opportunities to access industry-wide information, compared with a peripheral position in the global network, the significant amount of information that accrues to the central position in the global network can cause difficulties in isolating relevant information and transferring and applying it to new product development. Therefore, incremental new product launches that result from a central position in the global network depend on the firm's ability to transfer industry-wide information and complementary resources, such that the efficient use of industry-wide information allows it to promptly develop and launch new products along a similar market trajectory.

A highly interconnected ego network can facilitate such incremental new products that result from a central position in the global network. First, interconnected partners in a firm's ego network can better mediate industry-wide information from the global network. The redundant paths to the global network, through interconnected ego network partners, facilitate the transfer of information from the global network (Hansen 1999; Rowley, Behrens, and Krackhardt 2000). Second, cooperative norms and routines among ego network partners can facilitate their cooperation and improve the efficiency of their use of industry-wide information from the global network for their innovation activities. A firm embedded in the highly interconnected ego network then can better access and seize new product opportunities that accrue to it because of its central position in the global network.

H_{2a}: The positive effect of betweenness and closeness centrality on a firm's incremental new product launches is amplified by the firm's ego network density.

The abundance of industry-wide information available from the central position in a global network should exert a negative impact on breakthrough new product launches, and these negative effects might be amplified or relieved, depending on the ego network structure. In particular, launches of breakthrough new products that result from a central position in the global network benefit more from a lower level of ego network density. Shared norms and sanctions against opportunistic behavior in an interconnected ego network are likely to constrain a firm's innovative autonomy and willingness to apply industry-wide information gleaned from a global network position (Burt 1980). In contrast, a firm in a disconnected ego network might be less constrained by such norms and thus able to use the external information available in its global network more flexibly and transform it into more breakthrough new products. Its nonredundant ego network partners likely have different perceptions of and capabilities to use any given set of industry-wide information, which then increases opportunities to transform industry-wide information and resources from the global network into fundamental breakthroughs. For example, a firm might experiment more with industry-wide information from its global network when it also has more nonredundant ego network partners, such that it attempts discontinuous changes in product formulations, packaging, positioning, or merchandising. Such efforts could alleviate the negative effect of a central network position on breakthrough new product launches. Formally,

H_{2b}: The negative effect of betweenness and closeness centrality on a firm's breakthrough new product launches is amplified by the firm's ego network density.

Ego network diversity. Partners' characteristics influence how a firm learns through its interfirm collaborations (Sampson 2007). According to absorptive capacity research, firms can assimilate external knowledge only if it relates to their prior knowledge, which implies that similar partners should facilitate knowledge sharing and transfers (Lane and Lubatkin 1998; Mowery, Oxley, and Silverman 1996). Therefore, in an alliance network, a firm that is well embedded in its ego network, with more similar partners, can coordinate the processes of transferring and assimilating external information from the global network. The high costs of learning and coordinating with more diverse partners instead might slow down the absorption of the external resources that accrue to the central position in the global network. That is, ego network diversity could lower the efficiency with which the firm transforms resources gained from its central position into incremental new products. Thus, we make the following hypothesis:

H_{3a}: The positive effect of betweenness and closeness centrality on a firm's incremental new product launches is suppressed by the firm's ego network diversity.

With diverse ego network partners, a firm can arrange ideas and materials from its global network into novel combinations, a strategy that is likely to increase production of breakthrough new products. Using resources and capabilities sourced from the novel domains of its diverse ego network partners, a firm can develop multiple conceptualizations of problems and solutions and apply solutions from one domain to problems in another (Hargadon and Sutton 1997). This cross-fertilization of knowledge then can facilitate distant searches for significant changes to current products, which might complement industry-specific knowledge gained from the global network. Furthermore, working with partners with different backgrounds provides firms with access to diverse problem-solving heuristics, prompting them to explore new combinations of global network resources (Audia and Goncalo 2007). For example, working with an academic institution requires different routines than working with a for-profit business, and collaborating with big public firms can differ from collaborating with small firms (Baum, Calabrese, and Silverman 2000; Kalaignanam, Shankar, and Varadarajan 2007). Such varied collaboration heuristics might stimulate experimentation and searches for knowledge beyond an existing domain in the global network (Ahuja and Lampert 2001). Thus,

H_{3b}: The negative effect of betweenness and closeness centrality on a firm's breakthrough new product launches is suppressed by the firm's ego network diversity.

Moderating Effects of R&D Capability

In addition to using its ego network as a knowledge base from which to absorb global network resources, a firm must exploit its own knowledge. In particular, R&D capability accumulated from past R&D investments and innovation activities (Dutta, Narasimhan, and Rajiv 1999) can help a firm leverage its position in the global network. With this capability, the firm can identify and interpret relevant information and integrate it into its development of new products (Cohen and Levinthal 1990; Xiong and Bharadwaj 2011). For incremental new products, a firm with greater R&D capability accesses and transforms industry-wide knowledge more efficiently to improve its current products or services. Thus,

H_{4a}: The positive effect of betweenness and closeness centrality on a firm's incremental new product launches is amplified by the firm's R&D capability.

For breakthrough new products, R&D capability instead should stimulate the unique recombination of internally developed technologies and industry-wide knowledge from the global network, leading to innovative products. With a strong R&D capability, a firm can span technological boundaries in its new product development activities (Tushman and Katz 1980), which likely encourages novel knowledge recombination and integration (Grant 1996; Kogut and Zander 1992). In this sense, a firm's R&D capability can mitigate the lock-in effect of a central position in the industry-specific global network. By overcoming the constraining effect of a central position on the pursuit of fundamental changes, R&D capability should facilitate breakthrough new product launches by centrally positioned firms.

H_{4b}: The negative effect of betweenness and closeness centrality on a firm's breakthrough new product launches is suppressed by the firm's R&D capability.

METHODOLOGY

Empirical Setting

The CPG industry provides a suitable context for testing our conceptual model, for several reasons. First, interorganizational R&D collaborations among private and public firms, academic institutions, and government agencies are common and have expanded significantly since the late 1990s. First, for example, from 2000 to 2009, approximately 3,000 interorganizational R&D collaborations occurred among more than 400 firms and institutions. Second, firms in the CPG industry tend to emphasize new product development as a critical driver of performance and competitive advantage (Sorescu and Spanjol 2008). Third, this sector accounts for a substantial portion of the U.S. economy; in 2011, its spending exceeded \$2.4 trillion (Bureau of Economic Analysis 2011). The time frame for our data collection ran from 1990 to 2010.

Measures, Data, and Sample

We used archival methods to collect data about firms' global network centrality (closeness and betweenness), ego network density and diversity, R&D capability, breakthrough and incremental new product launches, and control variables. The data to test the hypotheses came from four different sources, enumerated next.

Global network measures. The network centrality data came from the SDC joint venture and alliance database, a comprehensive source that covers various formal interfirm relationships among public and private firms, academic and research institutions, and government agencies worldwide. In addition, the SDC database identifies the industry represented in interfirm relationships, so we can focus on the CPG industry. Among the various relational activities detailed by the SDC database, we gather data on interfirm relationships involving joint research collaboration, R&D, codevelopment, and other R&D-related activities. Our CPG industry network features all R&D collaborations between 1990 and 2010.

Consistent with prior studies (Stuart 2000; Swaminathan and Moorman 2009), we used a five-year window to create each firm's industry network. For example, to create the industry network for 2000, we used all interfirm relationships established between 1996 and 2000, inclusive. As prior studies have noted, the average life-span for technological resources is approximately five years (Pakes and Griliches 1984). As robustness checks, we also used four- and six-year windows.

Using the R&D collaborations of five-year periods as input to form global networks, we next collected two-mode data sets to support our construction of a one-mode network. The two-mode data sets were arranged as a firm-by-interfirm agreement matrix, in which $X_{ij} = 1$ if firm i participated in interfirm agreement j. We then converted the two-mode data into a one-mode network by creating a symmetric matrix in which the organizations appeared in the first column and the top row, both in the same order. Therefore, the number in a cell for [firm i, firm j] was equivalent to the number in the cell for [firm j, firm i], reflecting the number of interfirm agreements between these firms in the network. We use value, not just binary, data; the value denotes the number of interfirm agreements between two firms, which provides a proxy for the strength of their relationship and the information flows between them.

After constructing the global network, we calculated each firm's betweenness network centrality using the Freeman flow centrality measure (Freeman, Borgatti, and White 1991). Flow betweenness, by considering all the paths between firms in a network, appropriately responds to the nature of information flows in the global network composed of firms that are likely to be interconnected through various paths. In line with our data structure, a firm's network centrality reflects the proportion of information flows between other organizations that pass through that firm, modeled as follows:

$$(1) \qquad \text{Betweenness Centrality} = \frac{\sum_{j}^{n}\sum_{k}^{n} M_{jk}(x_i)}{\sum_{j}^{n}\sum_{k}^{n} M_{jk}},$$

where M_{jk} is the maximum information flow from firm j and k, and M_{jk} (x_i) is the maximum information flow from firm j and k that passes through firm i. The measure varies from 0 to 1.

To measure closeness centrality, we use the inverse of the sum of the geodesic distance between firm i and all other firms connected directly or indirectly to it. Thus, it reflects the binary network structure of the data (Freeman 1979). For a project i,

$$(2) \qquad \text{Closeness Centrality} = \frac{1}{\sum_{y \in U} d(i,j)},$$

where $d(i,j)$ is the geodesic distance (length of shortest path) between firms i and j, U is the set of all firms in the industry network, and $\sum_{y \in U} d(i,j)$ is the total number of geodesic connections between firm i and any other firm j that can be reached from i in the industry network. Although we calculated closeness and betweenness centrality for each organization, we only used the public firm data in the model analysis, because we have financial data for these firms. For example, in our sample, P&G has high betweenness and closeness centrality, but Johnson & Johnson, which is similar in size, shows relatively low betweenness and closeness centrality.

Ego network measures. Ego network density is the extent to which a firm's partners are connected to one another. Following Swaminathan and Moorman (2009), we measure the total number of unique relationships between a firm's partners, divided by the total number of possible ties among those partners. If a firm has five partners in its ego network, and these partners engage in four unique relationships, the ego network density measure equals .40 (4/10) because there are ten total possible relationships among five partners. In our 2001 data, whereas Unilever's partners appear less connected, General Mills' ego network partners are highly interconnected; four of its five partners connect directly.

Ego network diversity captures variation in the types of organizations in a firm's partner portfolio. We categorized each firm's R&D collaborations into three types: (1) with public firms, (2) with small private firms, and (3) with nonprofit organizations (e.g., universities, research institutions). Then, to calculate partner diversity, we relied on a Herfindahl index (Wuyts, Dutta, and Stremersch 2004) such that for firm i, we calculated the number of types (c) of partners and the number of times a firm's partners represented type j as $n_{j,c}$ (j = 1, ..., c). In turn, $p_{j,c} = n_{j,c}/\sum n_{j,c}$ represents the proportion of occurrences of type j, relative to the cumulative occurrences of all types. We square each p and take the sum over all national classes. Because we are interested in an index of ego network diversity, not its concentration, we subtract this sum from 1 (Wuyts, Dutta, and Stremersch 2004). For example, in 2002, Kimberly-Clark had only small private firms as partners, so it had low ego network diversity, but P&G's partners ranged across all three categories (see Figure 1), leading to high ego network diversity for that firm. Formally,

$$\text{(3)} \qquad \text{Ego network diversity} = 1 - \sum_{j=1}^{c} p_{j,c}^2.$$

Breakthrough and incremental new product launches. To measure a firm's new product launches, we used the ProductScan database, which has tracked new product introductions since the early 1980s. It compiles information about new products from a wide range of sources, including trade press, company websites, and visits to retail outlets. It also features the name, manufacturer, description, ingredients, and date of introduction of each product. Two advantages stem from this database (Sorescu and Spanjol 2008, p. 78):

> It does not suffer from survival bias. The data set includes a large sample of CPG publicly traded firms, regardless of their performance or eventual survival. It also contains all new products introduced by these firms, regardless of their eventual success in the market. A second advantage ... is that product introductions are recorded contemporaneously (rather than subsequently to introduction), ensuring that a potential memory bias does not affect which products are included in the sample.

For our study, the database also beneficially offers information about whether the product involves significant changes in any of the following areas: positioning, packaging, markets, merchandising, formulation, and technology. We provide specific examples in Table 2. Consistent with Sorescu and Spanjol (2008), we categorize new products as breakthrough if they involve significant differences from existing products in any of these areas, or incremental if they do not. For example, Avon introduced Tru Lie Concealer, the first interactive makeup system of modular, interlocking products, which involved a breakthrough in packaging.

We measured the number of each type of new product launched by a firm in each year. The aggregated trends of breakthrough and incremental new product launches over time (see Web Appendix A) show that the average number of breakthrough new product launches per firm per year has decreased slightly since the mid-1990s, whereas the number of incremental new product launches has increased slightly. Both variables are right-skewed, so we took log transformations.

R&D capabilities. We followed Dutta, Narasimhan, and Rajiv (1999) and adopted a production frontier model to measure marketing and R&D capabilities. These data came from several databases, including Compustat and the Delphion Patent Database. We detail the measures of R&D capability for each firm in Web Appendix B.

Control variables. We included several control variables. First, we controlled for ego network size, measured as the total number of partners in the firm's R&D collaborations over a five-year window. Second, we assessed technology diversity with a Herfindahl index, on the basis of the firm's granted patents in the previous five years (e.g., Fang, Palmatier, and Grewal 2011; Wuyts, Dutta, and Stremersch 2004), as provided by the Delphion Patent Database. Specifically, for each firm i, we calculated the number of national classes (c) of patents it earned each year and denoted the number of times that the firm's patents fell into a national class j as $n_{j,c}$ (j = 1, ..., c). Then, $p_{j,c} = n_{j,c}/\sum n_{j,c}$ represented the proportion of occurrences of national class j relative to the cumulative occurrence of all patents in those years. We squared each p and took the sum over all national classes, then subtracted this sum from 1 (Wuyts, Dutta, and Stremersch 2004). The technology diversity index equals 0 if the firm's patents all appear in a single class, and it moves toward 1 when the firm spreads its patents over more national classes. Third, we controlled for business diversity, or the extent to which a firm's activities span multiple business

Table 2

ILLUSTRATIVE EXAMPLES OF BREAKTHROUGH AND INCREMENTAL NEW PRODUCTS IN THE CPG INDUSTRY

Example	*Innovation Type*	*Details*
Yoplait Whips	Breakthrough (formulation)	New yogurt using significantly new formulations of high calcium and high vitamins, introduced by General Mills in 2002.
SK-II	Breakthrough (merchandising)	Skin care product line for which consumers must first visit an in-store "consultant" for an individualized skin analysis before they can purchase the products, introduced by P&G in 2003.
Tru Lie Concealer	Breakthrough (packaging)	First interactive makeup system of modular, interlocking products, introduced by Avon in 2003.
Liquid-Plumr Kitchen Clog Remover	Breakthrough (positioning)	First clog remover positioned for use in the kitchen, introduced by Clorox in 2003.
Clean & Clear Oil-Absorbing Sheets	Breakthrough (technology)	First absorbing sheets containing micropores that grab oil off the face, introduced by Johnson & Johnson in 1999.
Huggies Pull-Ups Disposable Training Pants	Breakthrough (market)	New disposable underwear category that created a new market, introduced by Kimberly-Clark in 1992.
Dove Firming Body Wash	Incremental	Based on early version, with minor changes in packaging (plastic bottle with a flip-up tab), introduced by Unilever in 2005.
Avon Naturals products, Red Rose & Peach scent	Incremental	A line extension to include a new scent, introduced by Avon in 2010.

segments. Although all the firms operate in the CPG industry, they focus on different segments. With data from the Compustat business segment databases, which cover a firm's sales revenues across segments (Steenkamp and Fang 2011), we used a Herfindahl index to calculate the proportion of a firm's sales revenue in each segment to total sales for the previous five years, then squared all proportions, summed them, and subtracted the sums from 1.

Several firm-level factors also likely affect breakthrough and incremental new product launches. We thus controlled for a firm's marketing capability (see Web Appendix B); firm size, measured as the log transformation of total assets; and the firm's net cash flow, which represents financial resources available to support new product development efforts. We took log transformations of the latter two variables. Finally, we controlled for each firm's financial leverage (ratio of its book debt to book value of total assets), which enhances performance (McAlister, Srinivasan, and Kim 2007). We gathered these data from Compustat.

The variable measurements and data sources are shown in Table 3. The descriptive statistics and correlations in Tables 4 and 5, respectively, together with the within- and between-firm standard deviations, reveal that although between-firm comparisons account for most of the variations, within-firm assessments also entail sufficient amounts of variation (approximately 10%–20%). This finding is not surprising, considering our "large N, small T" (i.e., many firms but relatively few time periods) data pattern. We obtained 1,087 observations of 91 publically traded firms between 1995 and 2010; the data from 1990 to 1994 served to create the industry networks. We took one-year lags between the independent and dependent variables.

Model Estimation

We adopted the system GMM to estimate our empirical model. To address the potential for reverse causality between network centrality and new product launches (Boulding and Staelin 1995), we sought an appropriate time lag and tested different lag structures, ranging from one to four years, as well as different combinations (e.g., one- and two-year lags; Steenkamp and Fang 2011). For both incremental and breakthrough new product launches, models with a one-year lag generated the best fit indices.

Variable endogeneity. When firms make decisions about network connections, they consider characteristics of potential partners such as closeness centrality, betweenness centrality, ego network density, and ego network diversity. These partner decisions are not made randomly, but, rather, firms select partners according to both the firms' assessments of how those partners can enhance the firms' new product launches and the firms' prior partner decisions. Therefore, we treat these variables, as well as relevant interactions involving these variables, as endogenous and adopt instrumental variables to address such endogeneity concerns.[1] As we detail in the following section, we instrument the variables in the first differencing equation using two-period lagged levels and the variables in the levels-levels equation using their own one-period lagged first differences (Roodman 2009).

Dynamic panel data structure. Our data have several important features. First, the structure indicates "large N, small T" panels. Second, the dependent variables are dynamic (i.e., breakthrough and incremental new product launches are somewhat persistent and depend on prior period observations). Third, our data may suffer endogeneity issues (i.e., regressors might correlate with prior or current period errors). Thus, our model requires a dynamic panel specification; dynamic models with lagged dependent variables cannot be estimated using ordinary least squares (Baltagi 2008).

Instead, following Arellano and Bond (1991) and Arellano and Bover (1995), we adopted a dynamic panel GMM estimation that can address dynamic dependent variables and endogeneity. A dynamic panel GMM generates sample moments from the data, which is appropriate when the error term and regressor distributions are not independent. To resolve these concerns, dynamic panel GMM uses first differencing to eliminate firm-specific fixed effects, then adopts two-period lagged levels as instrumental variables to alleviate simultaneity and dynamic endogeneity (Arellano and Bover 1995; Blundell and Bond 1998) (see Web Appendix C for specific model setup and moment conditions). Thus,

$$
\begin{aligned}
(4)\quad & \Delta\text{Breakthrough New Product Launches}_{i,t+1} \\
& = \theta_1 \Delta\text{Breakthrough New Product Launches}_{i,t} \\
& + \beta_{11}\Delta\text{Closeness Centrality}_{i,t} \\
& + \beta_{12}\Delta\text{Betweenness Centrality}_{i,t} \\
& + \beta_{13}\Delta\text{Ego Network Density}_{i,t} \\
& + \beta_{14}\Delta\text{Ego Network Diversity}_{i,t} \\
& + \beta_{15}\Delta\text{R\&D Capability}_{t} \\
& + \beta_{16}\Delta\text{Closeness Centrality}_{i,t} \\
& \times \Delta\text{Ego Network Density}_{i,t} \\
& + \beta_{17}\Delta\text{Closeness Centrality}_{i,t} \\
& \times \Delta\text{Ego Network Diversity}_{i,t} \\
& + \beta_{18}\Delta\text{Closeness Centrality}_{i,t} \\
& \times \Delta\text{R\&D Capability}_{t} \\
& + \Delta\text{Control variables}_{i,t} + \Delta e_{1,i,t+1}, \text{ and}
\end{aligned}
$$

$$
\begin{aligned}
(5)\quad & \Delta\text{Incremental New Product Launches}_{i,t+1} \\
& = \theta_2 \Delta\text{Incremental New Product Launches}_{i,t} \\
& + \beta_{21}\Delta\text{Closeness Centrality}_{i,t} \\
& + \beta_{22}\Delta\text{Betweenness Centrality}_{i,t} \\
& + \beta_{23}\Delta\text{Ego Network Density}_{i,t} \\
& + \beta_{24}\Delta\text{Ego Network Diversity}_{i,t} \\
& + \beta_{25}\Delta\text{R\&D Capability}_{t} \\
& + \beta_{26}\Delta\text{Closeness Centrality}_{i,t} \\
& \times \Delta\text{Ego Network Density}_{i,t} \\
& + \beta_{27}\Delta\text{Closeness Centrality}_{i,t} \\
& \times \Delta\text{Ego Network Diversity}_{i,t} \\
& + \beta_{28}\Delta\text{Closeness Centrality}_{i,t} \\
& \times \Delta\text{R\&D Capability}_{t} \\
& + \Delta\text{Control variables}_{i,t} + \Delta e_{2,i,t+1},
\end{aligned}
$$

where the control variables are Incremental New Product $\text{Launches}_{i,t-1}$, Breakthrough New Product $\text{Launches}_{i,t-1}$, Marketing $\text{Capability}_{i,t}$, Firm $\text{Size}_{i,t}$, Business $\text{Diversity}_{i,t}$, Net Cash $\text{Flow}_{i,t}$, Financial $\text{Leverage}_{i,t}$, and Technology $\text{Diversity}_{i,t}$.

[1]We thank an anonymous reviewer for this suggestion.

Table 3

SUMMARY OF MEASURES AND DATA SOURCES FOR KEY VARIABLES

Variable	*Measure*	*Data Source*
Dependent Variables		
Breakthrough new product launches	Number of breakthrough new products introduced by the firm per year	ProductScan
Incremental new product launches	Number of incremental new products introduced by the firm per year	ProductScan
Independent Variables		
Betweenness centrality	Betweenness measure of interfirm agreements established in the industry during the prior five years	SDC Joint Ventures and Alliances
Closeness centrality	Closeness measure of interfirm agreements established in the industry during the prior five years	SDC Joint Ventures and Alliances
Ego network density	Number of unique relationships between a firm's partners divided by the total number of possible ties among its partners	SDC Joint Ventures and Alliances
Ego network diversity	1 – Herfindahl index, based on the types of partners (public firms, private firms, and nonprofit organizations) during the prior five years	SDC Joint Ventures and Alliances
R&D capability	Efficient frontier using technology as output and R&D-related assets as input	Delphion Patent Database; Compustat
Control Variables		
Marketing capability	Efficient frontier using sales as output and marketing-related assets as input	Delphion Patent Database; Compustat
Ego network size	The total number of partners that a firm's R&D collaborations involved during the prior five years	SDC Joint Ventures and Alliances
Firm size	Log transformation of total assets	Compustat
Business diversity	1 – Herfindahl index, based on firm sales across multiple business segments during the prior five years	Compustat business segment
Net cash flow	Log transformation of a firm's net cash flow	Compustat
Financial leverage	Ratio of a firm's book debt to its book value of total assets	Compustat
Technology diversity	1 – Herfindahl index, based on national classes of a firm's granted patents in the prior five years	Delphion Patent Database

System GMM. The dynamic GMM estimation has two potential limitations. First, the lagged levels may be poor instruments for first differenced variables, especially if the variables are close to a random walk (Arellano and Bover 1995; Blundell and Bond 1998). Second, the first differencing of variables may lead to inefficient estimations, due to the loss of temporal variations (Arellano and Bover 1995). Therefore, Arellano and Bover (1995) and Blundell and Bond (1998) propose a system GMM estimator that includes both first differencing and levels models. In particular, we instrument the variables in the levels-levels equation using their own one-period lagged first differences (Roodman 2009):

$$(6)\quad \begin{aligned} &\text{Breakthrough New Product Launches}_{i,t+1} \\ &= \alpha_{1\alpha} + \theta_3 \text{Breakthrough New Product Launches}_{i,t} \\ &+ \alpha_{11}\text{Closeness Centrality}_{i,t} \\ &+ \alpha_{12}\text{Betweenness Centrality}_{i,t} \\ &+ \alpha_{13}\text{Ego Network Density}_{i,t} \\ &+ \alpha_{14}\text{Ego Network Diversity}_{i,t} \\ &+ \alpha_{15}\text{R\&D Capability}_{t} \\ &+ \alpha_{16}\text{Closeness Centrality}_{i,t} \\ &\times \text{Ego Network Density}_{i,t} \\ &+ \alpha_{17}\text{Closeness Centrality}_{i,t} \\ &\times \text{Ego Network Diversity}_{i,t} \\ &+ \alpha_{18}\text{Closeness Centrality}_{i,ti} \\ &\times \text{R\&D Capability}_{t} \\ &+ \text{Control variables}_{i,t} + \eta_{1i} + e_{1,i,t+1}, \text{ and} \end{aligned}$$

$$(7)\quad \begin{aligned} &\text{Incremental New Product Launches}_{i,t+1} \\ &= \alpha_{2\alpha} + \theta_4 \text{Incremental New Product Launches}_{i,t} \\ &+ \alpha_{21}\text{Closeness Centrality}_{i,t} \\ &+ \alpha_{22}\text{Betweenness Centrality}_{i,t} \\ &+ \alpha_{23}\text{Ego Network Density}_{i,t} \\ &+ \alpha_{24}\text{Ego Network Diversity}_{i,t} \\ &+ \alpha_{25}\text{R\&D Capability}_{t} \\ &+ \alpha_{26}\text{Closeness Centrality}_{i,t} \\ &\times \text{Ego Network Density}_{i,t} \\ &+ \alpha_{27}\text{Closeness Centrality}_{i,t} \\ &\times \text{Ego Network Diversity}_{i,t} \\ &+ \alpha_{28}\text{Closeness Centrality}_{i,t} \\ &\times \text{R\&D Capability}_{t} \\ &+ \text{Control variables}_{i,t} + \eta_{2i} + e_{2,i,t+1} \end{aligned}$$

where the control variables are Incremental New Product Launches$_{i,t-1}$, Breakthrough New Product Launches$_{i,t-1}$, Marketing Capability$_{i,t}$, Firm Size$_{i,t}$, Business Diversity$_{i,t}$, Net Cash Flow$_{i,t}$, Financial Leverage$_{i,t}$, Technology Diversity$_{i,t}$, and year dummies. For the system GMM, we estimated Equations 4 and 6 together and Equations 5 and 7 together. We tested for the validity of the instruments using Hansen's (1982) test of overidentifying restrictions, with the requirement that the J-statistic does not reject the null hypothesis. The results failed to reject the null hypothesis that the model specification meets the moment condition, so the instruments appear valid (Table 6). We adopted Stata's xtabond2 procedure to estimate the models.

Table 4
DESCRIPTIVE STATISTICS

Variable	*M*	*SD*	*Between-Firm SD*	*Within-Firm SD*
1. Betweenness centrality	.0312	.0124	.0112	.0029
2. Closeness centrality	.0501	.0343	.0331	.0034
3. Ego network density	.2018	.2201	.2039	.0359
4. Ego network diversity	.1621	.0665	.0574	.0076
5. Breakthrough new product launches	1.5204	1.1820	.9837	.3543
6. Incremental new product launches	10.4521	5.2505	4.9489	1.1092
7. R&D capability	.0287	.0772	.0613	.0169
8. Marketing capability	.0422	.1602	.1584	.0342
9. Ego network size	5.9123	7.2123	6.9893	1.0493
10. Firm size	4.1113	1.8512	1.8403	.1031
11. Business diversity	.2343	.2918	.2354	.0828
12. Net cash flow	3.1823	4.2432	3.7930	.6842
13. Financial leverage	.2734	.2614	.2394	.0569
14. Technology diversity	.5117	.1976	.1590	.0694

MODEL ESTIMATION AND RESULTS

Model-Free Evidence

Table 5 shows that network centrality (closeness and betweenness) correlates negatively with breakthrough new product launches but positively with incremental new product launches, consistent with H_1. In Figures 3 and 4, we present some model-free evidence. In particular, we first take the first differencing of betweenness centrality, closeness centrality, and incremental and breakthrough new product launches. We present model-free correlations dependent on levels of ego network density and diversity and R&D capability. Thus, we are interested in the correlations between within-firm temporal variations of the two metrics. In Figure 3, Panel A, we show that when ego network density is low (one standard deviation below the mean), the negative correlation between betweenness centrality and breakthrough new product launches (–.011) is substantially flatter than that negative correlation (–.064) when density is high (one standard deviation above the mean. The positive correlation between betweenness centrality and incremental new product launches is substantially higher in conditions of high (.078) versus low (.042) ego network density. For ego network diversity, in Figure 3, Panel B, we show that when diversity is high (one standard deviation above the mean), the negative correlation between betweenness centrality and breakthrough new product launches (.007, n.s.) is substantially flatter than that negative correlation (–.059) when diversity is low (one standard deviation below the mean). The positive correlation of betweenness centrality and incremental new product launches is substantially lower when diversity is high (.036) than when it is low (.079). In addition, Figure 3, Panel C, indicates that when R&D capability is high (one standard deviation above the mean), the correlation of betweenness centrality and breakthrough new product launches (.008, n.s.) is substantially flatter than that negative correlation (–.032) when R&D capability is low (one standard deviation below the mean), and the positive correlation of betweenness centrality with incremental new product launches is higher with high R&D capability (.069) than with low R&D capability (.020, n.s.). The correlations

Table 5
CORRELATIONS

	Correlations													
Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*
1. Betweenness centrality	1.00													
2. Closeness centrality	.3611	1.00												
3. Ego network density	.1601	.1912	1.00											
4. Ego network diversity	.2123	.2887	–.0856	1.00										
5. Breakthrough new product launches	–.0710	–.1033	–.0521	.1221	1.00									
6. Incremental new product launches	.1101	.1602	.0812	–.0444	.6143	1.00								
7. R&D capability	.0853	.0676	.0221	.1423	.0923	.1012	1.00							
8. Marketing capability	.0323	.0255	–.0356	.0567	.0491	.0701	.2335	1.00						
9. Ego network size	.2304	.3432	–.2646	.4305	–.1410	.1712	.1404	–.0344	1.00					
10. Firm size	.3423	.3056	.1087	.2967	.1934	.2999	.0922	.1404	.3101	1.00				
11. Business diversity	.0283	.0419	–.0736	.0837	.0238	.1193	.0248	.0783	.1028	.1637	1.00			
12. Net cash flow	.0810	.1123	.0423	.1377	.1143	.1743	.0723	.0536	.2025	.4826	–.0482	1.00		
13. Financial leverage	.0201	.0901	.0124	.0224	–.0356	–.0451	–.0509	–.0880	.0124	–.1446	.1320	–.0816	1.00	
14. Technology diversity	.1256	.1943	–.0325	.1878	.0913	.1185	–.0467	.0446	.1227	.1842	.1893	.1164	.0526	1.00

Notes: Values are significant at $p < .05$ for $r > .06$ and $r < -.06$.

Table 6

EFFECTS OF GLOBAL AND EGO NETWORKS ON NEW PRODUCT LAUNCHES

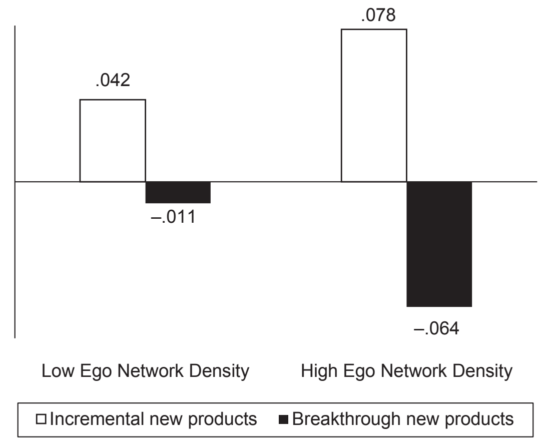
			Incremental New Product Launches$_{t+1}$					Breakthrough New Product Launches$_{t+1}$	
Variable	*Hypothesis*	*Model 1: Levels-Levels*	*Model 2: Levels-Levels*	*Model 3: Differences-Differences*	*Model 4: Differences-Differences*	*Model 5: Levels-Levels*	*Model 6: Levels-Levels*	*Model 7: Differences-Differences*	*Model 8: Differences-Differences*
Independent Variables									
Closeness Centrality$_t$	H_1	.9345***	.9204**	4.5343***	4.1812**	−.1811	−.1573	−.5518	−.5328
Betweenness Centrality$_t$	H_1	3.0193	2.8183	13.1232	11.4893	−1.1894***	−1.1537**	−5.5789***	−5.5374**
Ego Network Density$_t$		.0818***	.0498*	.1731***	.1648**	−.0151	−.0120	−.0404	−.0389
Ego Network Diversity$_t$		.1006	.0929	.4746	.4122	.0358	.0328	.1454**	.1239*
R&D Capability$_t$		.3205**	.2858*	1.3843**	1.2539*	.0482**	.0402**	.1103	.0976
Moderating Effects									
Closeness Centrality$_t$ × Ego Network Density$_t$	H_2		1.2520**		4.6182**		−.0913		−.3592
Closeness Centrality$_t$ × Ego Network Diversity$_t$	H_3		−3.0356		−10.5482		.5732***		1.8602**
Closeness Centrality$_t$ × R&D Capability$_t$	H_4		3.0210		9.5129		.3123		1.5702
Betweenness Centrality$_t$ × Ego Network Density$_t$	H_2		8.1029***		24.3163***		−.9576**		−3.0291**
Betweenness Centrality$_t$ × Ego Network Diversity$_t$	H_3		−22.1021**		−91.1032		2.8893**		12.1392**
Betweenness Centrality × R&D Capability$_t$	H_4		26.8647***		99.7638**		3.7983		9.7002
Control Variables									
Incremental New Product Launches$_t$		.2875***	.2801***	.6778***	.6582***	.0513**	.0501**	.1210*	.1102*
Breakthrough New Product Launches$_t$		.0447	.0354	.0918	.0907	.3319**	.3134**	.9103***	.8703***
Marketing Capability$_t$		.1389**	.1311*	.4749*	.4701*	.0179	.0172	.0611	.0585
Ego Network Size$_t$		.0179**	.0164**	.0523**	.0508**	.0007	.0007	.0025	.0021
Firm Size$_t$		.0885***	.0819***	.2335***	.2203***	.0085***	.0079***	.0246***	.0221***
Business Diversity$_t$		.0741**	.0731**	.1954**	.1864**	.0086	.0082	.0151	.0147
Net Case Flow$_t$		.0072	.0064	.0307	.0283	.0004	.0005	.0016	.0013
Financial Leverage$_t$		.0334	.0317	.1522	.1476	.0061	.0059	.0115	.0107
Technology Diversity$_t$		−.0969*	−.0941*	−.1773	−0.1692	.0073	.0071	.0199*	.0191*
Wald χ^2		363.2948***	401.1983***	11.3843***	14.9947***	326.2933***	366.1823***	10.5938***	12.5203***
AR(1)		−3.6948***	−3.7938***	−2.9892**	−3.0329**	−3.2455***	−3.5103***	−2.7239**	−2.9903**
AR(2)		1.0137	1.0204	.7104	.7538	1.6291	1.6787	.8583	.8967
Hansen's overidentification test (J-test)		103.9822	106.1039	116.9832	122.4948	99.1938	105.3838	105.4637	109.1573
p-Value for J-test		.1930	.1637	.1573	.1478	.1959	.1727	.1702	.1627

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: For brevity, this table does not include the results for the year dummy.

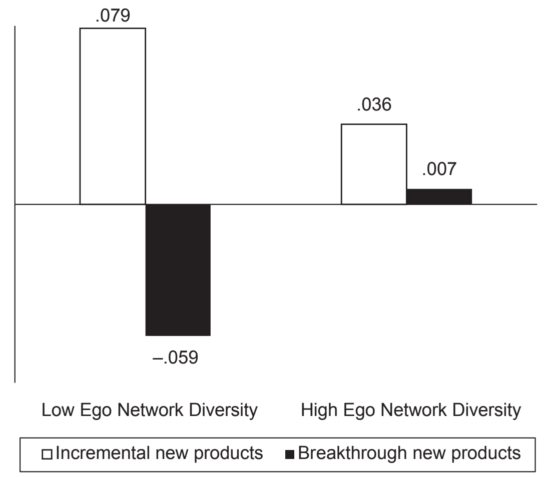
Figure 3

CORRELATION BETWEEN BETWEENNESS CENTRALITY AND NEW PRODUCT LAUNCHES

A:At Different Levels of Ego Network Density



B: At Different Levels of Ego Network Diversity



C: At Different Levels of R&D Capability

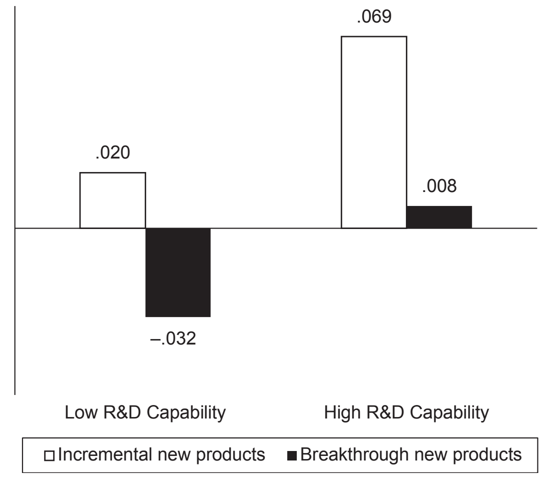
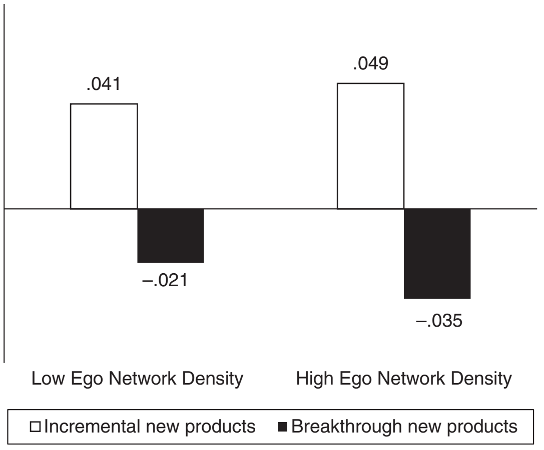


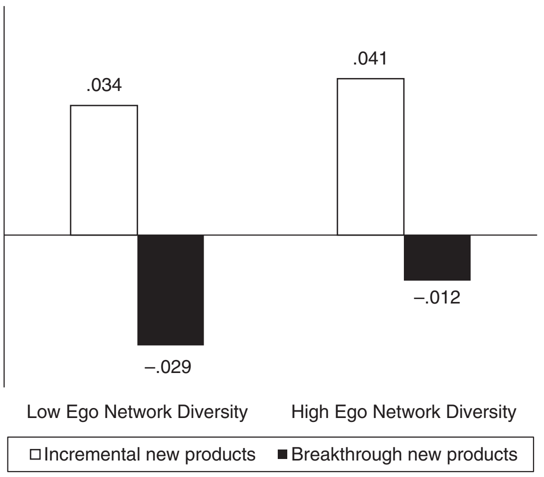
Figure 4

CORRELATION BETWEEN CLOSENESS CENTRALITY AND NEW PRODUCT LAUNCHES

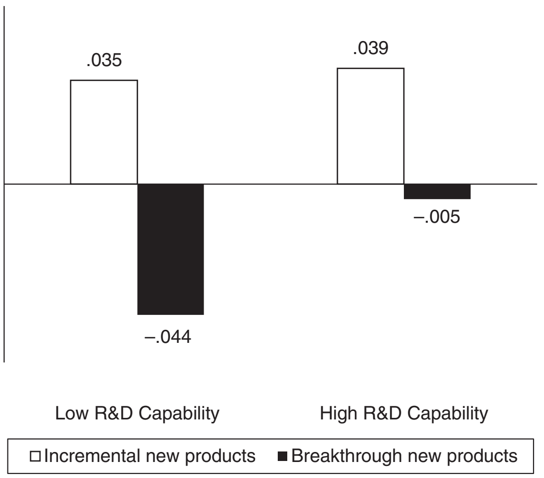
A: At Different Levels of Ego Network Density



B: At Different Levels of Ego Network Diversity



C: At Different Levels of R&D Capability



of closeness centrality with new product launches in Figure 4 indicate similar patterns; the results provide some evidence in support of our hypotheses, even before we test the model.

Estimation Results

In Models 1–8 in Table 6, values of the Wald χ^2 statistic, which assesses whether the proposed model specifications predict breakthrough and incremental new product launches, are significant, in support of the model specifications. We also examine first- and second-order autoregressive (AR) statistics, AR(1) and AR(2), to test for serial correlation in the error terms, because the system GMM assumes that first-order serial correlation is present but second-order serial correlation is not (Arellano and Bond 1991). Our results reject AR(1) (with the null hypothesis that there is no first-order serial correlation) but fail to reject AR(2) (with the null hypothesis that there is no second-order serial correlation), in further support of our model specifications. We performed the augmented Dickey–Fuller unit-root test to address the null hypothesis (Enders 1995), and the results rejected the presence of unit roots for all variables. Therefore, all variables are stationary.

Because the level-in-level and difference-in-difference models generate highly consistent results, we focus on the level-in-level model results in this discussion. In Model 1, for incremental new product launches, closeness centrality has a positive effect ($\beta = .9345$, $p < .01$), whereas betweenness centrality has no significant effect ($\beta = 3.0193$, n.s.). For breakthrough new product launches, closeness centrality has no significant effect ($\beta = -.1811$, n.s.), but betweenness centrality has a negative effect ($\beta = -1.1894$, $p < .01$). These findings provide partial support of $H_{1a–b}$, in which we suggest that a firm's central position in the global network enhances incremental new products launches but hinders breakthrough new products.

Regarding the moderating effects, Model 2 also shows that ego network density positively moderates the effects of closeness and betweenness centrality on incremental new product launches ($\beta = 1.2520$, $p < .05$ and $\beta = 8.1029$, $p < .01$, respectively), in support of H_{2a}. In Model 6, ego network density negatively moderates the effect of betweenness centrality on breakthrough new product launches ($\beta = -.9576$, $p < .05$), which affirms H_{2b}. However, for closeness centrality, we find no moderating effect of ego network density. Moreover, in Model 2, ego network diversity negatively moderates the effect of betweenness centrality on incremental new product launches ($\beta = -22.1021$, $p < .05$), whereas in Model 6, it positively moderates the effect of closeness and betweenness centrality on breakthrough new product launches ($\beta = .5732$, $p < .01$ and $\beta = 2.8893$, $p < .05$, respectively). These findings are consistent with $H_{3a–b}$. Finally, in Model 2, R&D capability positively moderates the effect of betweenness centrality on incremental new product launches ($\beta = 26.8647$, $p < .01$), in support of H_{4a}. We cannot confirm H_{4b}, however, because R&D capability has no significant moderating effect on breakthrough new product launches. We find no moderating effect of R&D capability on closeness centrality.

Validation Analyses

To enhance confidence in our results, we conducted validation analyses with (1) alternative time windows for the ego and industry global networks, (2) betweenness centrality adjusted by relationship type, (3) interfirm R&D agreements adjusted by time depreciation, (4) an alternative measure of breakthrough new product launches, (5) an alternative measure of betweenness/closeness centrality after removing the variation explained by ego network diversity and density, (6) a nonlinear GMM model estimation, (7) a difference-in-difference-only model with joint estimation, (8) eigenvector centrality of partners included as a control variable, (9) models that explore the nonlinear effects of betweenness and closeness centrality on a firm's new product launches, (10) bootstrap standard errors to address potential weak instrument issues, and (11) system GMM with a "collapsed" instrument approach to address the issue of instrument proliferation. As we detail in Web Appendix D, the overall patterns hold across all these validation analyses, in support of our empirical results.

Managerial Simulation

Finally, we sought to apply these results to answer a managerially critical question: How should firms, depending on their R&D capabilities, structure their ego and global networks to optimize their breakthrough and incremental new product launches? In a scenario analysis, we used a baseline, "typical" firm with mean values for the ego network factors, industry network factors, and control variables, adopting the level-in-level model approach (Table 6). We then estimated 16 scenarios with higher and lower values of betweenness centrality, ego network density, ego network diversity, and R&D capability. The high conditions were two standard deviations above the mean; the low conditions were two standard deviations below it. For each condition, we present the best scenarios in Table 7.

First, for breakthrough new product launches, the optimal strategy features low global network betweenness centrality and ego network density but high ego network diversity. This strategy, which we refer to as a "breakthrough new product–driving network strategy," generated 24.84% more breakthrough new products than the baseline condition for firms with both high and low R&D capabilities. Such a strategy was employed by General Mills during 1995–2000, when it established relationships with different types of organizations (public, private, and others), mostly located outside the United States. These partners were not highly connected with one another and had few connections with organizations in other parts of the world. This strategy, however, produces poor results for incremental new product launches: 17.34% lower than the baseline for firms with high R&D capability, and 13.02% lower for those with low R&D capability.

Second, for incremental new product launches, the optimal strategy is to occupy a central position in the industry network (high betweenness), with high ego network density but low ego network diversity. Compared with the baseline condition, the increase in incremental new products in this case was 18.12% for firms with high R&D capability and 14.21% for firms with low R&D capability. However, this

Table 7

MANAGERIAL SIMULATION RESULTS: EGO AND GLOBAL NETWORK CONDITIONS FOR NEW PRODUCT LAUNCHES DEPENDING ON R&D CAPABILITY

	Breakthrough New Product–Driving Network Strategy		*Incremental New Product–Driving Network Strategy*		*Balanced New Product–Driving Network Strategy*	
	High R&D Capability	*Low R&D Capability*	*High R&D Capability*	*Low R&D Capability*	*High R&D Capability*	*Low R&D Capability*
Network Conditions						
Global network betweenness centrality	Low	Low	High	High	High	Low
Ego network density	Low	Low	High	High	Low	High
Ego network diversity	High	High	Low	Low	High	Low
Outcomes in Comparison with Baseline Condition						
Breakthrough new product launches	+24.87%	+24.87%	−14.82%	−14.82%	+18.04%	+9.94%
Incremental new product launches	−17.34%	−13.02%	+18.12%	+14.21%	+14.04%	+7.94%
Examples	General Mills in 1995–2000	General Mills in 1995–2000	Clorox since the late 1990s	Clorox since the late 1990s	P&G since the early 2000s	Kimberly-Clark in the late 2000s

"incremental new product–driving network strategy" was the worst strategy for breakthrough new product launches, which decreased by 14.82% compared with the baseline for firms with both high and low R&D capabilities. Clorox has pursued such a strategy since the late 1990s. During 2001–2005, it established relationships with firms in central positions in the CPG industry, such as Unilever, leading to Clorox's high betweenness centrality. These partners are highly interconnected and mostly large, public firms, such that they lack diversity.

Some scenarios might deliver strong results for both breakthrough and incremental new product launches. For firms with high R&D capability, a central position in industry networks, low ego network density, and high network diversity generated more breakthrough (18.04%) and incremental (14.04%) new products than the baseline condition. This strategy is exemplified by P&G's approach since the early 2000s, with which it has established a wide range of partners in central positions in their respective domains. These partners range from private to public organizations, and they are not extensively connected. For firms with low R&D capability, a peripheral position in the industry network, high ego network density, and low ego network diversity generated 9.94% more breakthrough new product launches, compared with the baseline, as well as 7.94% more incremental new product launches. Kimberly-Clark adopted such a strategy in the late 2000s by establishing relationships with mostly private firms in paper-related products. These firms are highly connected among themselves but not well connected with other industry participants. Both scenarios produce positive returns; although these "balanced new product-driving network strategies" are not optimal for either breakthrough or incremental new product launches, they provide an excellent compromise option.

DISCUSSION

We examine the effects of global network position on breakthrough and incremental new product launches, along with the moderating roles of ego networks and R&D capabilities. The findings provide important insights for network and new product literature, as well as managerial recommendations for leveraging network positions to promote new product launches.

Theoretical Implications

Whereas prior research has highlighted the benefits of central network positions for innovation, our finer-grained model reveals some boundary conditions. Betweenness centrality implies that a firm acts as a broker between other firms; closeness centrality indicates that it can easily access other parts of the industry through few intermediaries. Although both forms facilitate access to information, innovation outcomes also depend on the type of innovation (i.e., breakthrough vs. incremental). A central position in an industry helps a firm create incremental new product launches, but it harms breakthrough new product launches. Therefore, network centrality is a double-edged sword that enhances a firm's access to industry-specific information and promotes incremental new product launches but also constrains the firm's noncumulative, competency-destroying innovations and reduces its breakthrough new product launches. Researchers must acknowledge the types of new products associated with network positions; focusing on an aggregated effect while neglecting the specific type of new products may lead to an incomplete or biased picture of the link between network centrality and product launches.

This study also provides important insights into the interactive relationships of ego and global networks with new product launches, rather than focusing on either ego or global networks. A firm relies on its direct partners to access resources from indirect partners in the global network (Ahuja 2000), and our results show that a firm with more interconnected or homogeneous ego networks can produce more incremental new products from its central position in a global network. By pooling resources with its partners, a firm becomes more efficient in acquiring and exploiting external information to derive incremental new products. An ego network with less interconnected or more diverse partners also can help a centrally located firm avoid the hazards for its breakthrough new product launches, because in this case, it is less constrained by existing norms or routines and has more flexibility to experiment with resources from the global network.

By noting the inconsistent effect of ego and global networks on breakthrough and incremental new products, we help clarify the conditions that enhance launches of each type. The inconsistent effects on breakthrough and incremental new product launches reveal that the effects of any single network property cannot define network strategies that will benefit both types. Rather, as our managerial simulation shows, a network strategy that produces the highest returns for one type of new product might generate negative returns for another. A systematic approach to aligning ego and global network properties, depending on a firm's R&D capability, provides a compromise that contributes to both types of new product launches. We specify several configurations that can ensure balanced ego/global network strategies for both breakthrough and incremental new product launches, even if they are not optimal for either type individually.

Managerial Implications

The structure of alliance networks is path dependent and cumulative over time, through prior alliance activities (Gulati and Gargiulo 1999). Although networks, particularly global networks, are not entirely within a firm's control, a firm can strive to build its ego network in different ways, depending on its position in the global network. Accordingly, we offer several recommendations for managers. In particular, they should be cognizant that being located centrally in an industry network does not guarantee strong new product performance; it can even be detrimental, particularly for breakthrough new products, which require the firm to think outside the box and actively explore new resources and competencies. We describe optimal network formation strategies that reflect considerations of both ego and global network factors as well as R&D capabilities, which provide the relative impact on both breakthrough and incremental new product launches compared to the average firm in the sample. We provide an example of a large CPG firm that has utilized each strategy in Table 7.

However, breakthrough or incremental new product launches achieved by pursuing such network formation strategies also might come at the cost of sacrificing launches of other type of new products. It also is possible to align global and ego networks to achieve both breakthrough and incremental new products, depending on R&D capability: firms with higher centrality in the global network can achieve the balance between breakthrough and incremental new products by building lower density and higher diversity in their ego network as well as higher R&D capability. Alternatively, firms with lower centrality in the global network can achieve balance by building higher density and lower diversity in their ego network as well as lower R&D capability. Accordingly, when managers build ego networks with directly connected partners, they should attend to their firms' positions in the overall industry network. We strongly emphasize the need to understand the industry network structure and the firm's unique position in that network. Using network analysis and available industry data, a firm can paint a more realistic picture of its industry network.

Limitations and Further Research

This research is subject to several limitations that suggest research directions. First, we employed a single industry context, which minimizes potential confounds across multiple industries (e.g., different innovation strategies, varying relationship-building practices). Additional research could extend our findings beyond CPG to other industries, cultures, and networks and thereby test the generalizability of our results. Especially worthwhile would be tests of the relative importance of positive versus negative network perspectives in countries in which intellectual property protection is weak, although such a study would require a different research design and possibly a different operationalization of innovation.

Second, we focused on the CPG industry as a network boundary that influences the scope of search activities and thus innovation performance. However, this focus may lead to potential problems by defining network boundaries either too narrowly, which likely fails to reflect information flows that actually occur in a global network, or too broadly, which causes the risks of including irrelevant information flows. Future studies that apply network boundaries defined at varying levels are expected to enrich our understanding of global network and its impact on innovation.

Third, although we validated our choice of instruments both theoretically and empirically, the results of this study need to be interpreted carefully. It is important to recognize the possible downside of weak and/or too many instruments that lead to smaller standard errors.

Fourth, Baum, Calabrese, and Silverman (2000) find that industry network composition affects a firm's performance. Further research should test how network-level characteristics, such as composition and density, interact with firm-level network centrality to affect innovation, using data from multiple industries. For example, in a loosely connected or densely connected industry network, the effectiveness of a firm's network centrality may differ.

REFERENCES

Ahuja, Gautam (2000), "Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study," *Administrative Science Quarterly*, 45 (September), 425–55.

——— and Curba Morris Lampert (2001), "Entrepreneurship in the Large Corporation: A Longitudinal Study of How Established Firms Create Breakthrough Inventions," *Strategic Management Journal*, 22 (6/7), 521–43.

Ahuja, Manju K., Dennis F. Galletta, and Kathleen M. Carley (2003), "Individual Centrality and Performance in Virtual R&D Groups: An Empirical Study," *Management Science*, 49 (1), 21–38.

Arellano, Manuel and Stephen Bond (1991), "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies*, 58 (2), 277–97.

——— and Olympia Bover (1995), "Another Look at the Instrumental Variable Estimation of Error-Components Models," *Journal of Econometrics*, 68 (1), 29–51.

Audia, Pino G. and Jack A. Goncalo (2007), "Past Success and Creativity over Time: A Study of Inventors in the Hard Disk Drive Industry," *Management Science*, 53 (1), 1–15.

Baltagi, Badi (2008), *Econometric Analysis of Panel Data*. New York: John Wiley & Sons.

Baum, Joel A.C., Tony Calabrese, and Brian S. Silverman (2000), "Don't Go It Alone: Alliance Network Composition and Startups' Performance in Canadian Biotechnology," *Strategic Management Journal*, 21 (3), 267–94.

Blundell, Richard and Stephen Bond (1998), "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics*, 87 (1), 115–43.

Boulding, William and Richard Staelin (1995), "Identifying Generalizable Effects of Strategic Actions on Firm Performance: The Case of Demand-Side Returns to R&D Spending," *Marketing Science*, 14 (3), G222–36.

Brass, Daniel J., Kenneth D. Butterfield, and Bruce C. Skaggs (1998), "Relationships and Unethical Behavior: A Social Network Perspective," *Academy of Management Review*, 23 (1), 14–31.

Bureau of Economic Analysis (2011), "National Income and Product Accounts Table 2.3.5: Personal Consumption Expenditures by Major Type of Product," (accessed February 1, 2014), [available in Section 2 under "1969–Present" at http://www.bea.gov//national/nipaweb/DownSS2.asp].

Burt, Ronald S. (1980), "Autonomy in a Social Topology," *American Journal of Sociology*, 85 (4), 892–925.

Calvey, Mark (2012), "New Products Help Clorox Achieve 5% Growth," *San Francisco Business Times*, (July 6), [available at http://www.bizjournals.com/sanfrancisco/print-edition/2012/07/06/new-products-help-clorox-achieve-5.html].

Chandy, Rajesh K. and Gerard J. Tellis (1998), "Organizing for Radical Product Innovation: The Overlooked Role of Willingness to Cannibalize," *Journal of Marketing Research*, 35 (November), 474–87.

Cohen, Wesley M. and Daniel A. Levinthal (1990), "Absorptive Capacity: A New Perspective on Learning and Innovation," *Administrative Science Quarterly*, 35 (1), 128–52.

Coleman, James S. (1990), *Foundation of Social Theory*. Cambridge, MA: Belknap.

Cui, Anna Shaojie and Gina O'Connor (2012), "Alliance Portfolio Resource Diversity and Firm Innovation," *Journal of Marketing*, 76 (July), 24–43.

Dodgson, Mark, David Gann, and Ammon Salter (2006), "The Role of Technology in the Shift Towards Open Innovation: The Case of Procter & Gamble," *R&D Management*, 36 (3), 333–46.

Dutta, Shantanu, Om Narasimhan, and Surendra Rajiv (1999), "Success in High-Technology Markets: Is Marketing Capability Critical?" *Marketing Science*, 18 (4), 547–68.

Enders, Walter (1995), *Applied Econometric Time Series*. New York: John Wiley & Sons.

Ettlie, John E. (1983), "Organizational Policy and Innovation Among Suppliers to the Food Processing Sector," *Academy of Management Journal*, 26 (1), 27–44.

Fang, Eric (Er) (2008), "Customer Participation and the Trade-Off Between New Product Innovativeness and Speed to Market," *Journal of Marketing*, 72 (July), 90–104.

———, Robert W. Palmatier, and Rajdeep Grewal (2011), "Effects of Customer and Innovation Asset Configuration Strategies on Firm Performance," *Journal of Marketing Research*, 48 (May), 587–602.

Freeman, Linton C. (1979), "Centrality in Social Networks Conceptual Clarification," *Social Networks*, 1 (3), 215–39.

———, Stephen P. Borgatti, and Douglas R. White (1991), "Centrality in Valued Graphs: A Measure of Betweenness Based on Network Flow," *Social Networks*, 13 (2), 141–54.

Grabher, Gernot (1993), "The Weakness of Strong Ties: The Lock-In of Regional Development in the Ruhr Area," in *The Embedded Firm: On the Socioeconomics of Industrial Networks*, Gernot Grabher, ed. London: Routledge, 255–77.

Grant, Robert M. (1996), "Toward a Knowledge-Based Theory of the Firm," *Strategic Management Journal*, 17, 109–22.

Griliches, Zvi, ed. (1984), *R&D, Patents, and Productivity*. Chicago: University of Chicago Press.

Gulati, Ranjay and Martin Gargiulo (1999), "Where Do Interorganizational Networks Come From?" *American Journal of Sociology*, 104 (5), 1439–93.

Han, Jin K, Namwoon Kim, and Hong-Bumm Kim (2001), "Entry Barriers: A Dull-, One-, or Two-Edged Sword for Incumbents? Unraveling the Paradox from a Contingency Perspective," *Journal of Marketing*, 65 (January), 1–14.

Hansen, Lars Peter (1982), "Large Sample Properties of Generalized Method of Moments Estimators," *Econometrica*, 50 (4), 1029–54.

Hansen, Morten T. (1999), "The Search-Transfer Problem: The Role of Weak Ties in Sharing Knowledge Across Organization Subunits," *Administrative Science Quarterly*, 44 (1), 82–111.

Hargadon, Andrew and Robert I. Sutton (1997), "Technology Brokering and Innovation in a Product Development Firm," *Administrative Science Quarterly*, 42 (4), 716–49.

Jap, Sandy D. (1999), "Pie-Expansion Efforts: Collaboration Processes in Buyer–Supplier Relationships," *Journal of Marketing Research*, 36 (December), 461–75.

Kalaignanam, Kartik, Venkatesh Shankar, and Rajan Varadarajan (2007), "Asymmetric New Product Development Alliances: Win-Win or Win-Lose Partnerships?" *Management Science*, 53 (3), 357–74.

Kogut, Bruce (2000), "The Network as Knowledge: Generative Rules and the Emergence of Structure," *Strategic Management Journal*, 21 (3), 404–25.

——— and Udo Zander (1992), "Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology," *Organization Science*, 3 (3), 383–97.

Lane, Peter J. and Michael Lubatkin (1998), "Relative Absorptive Capacity and Interorganizational Learning," *Strategic Management Journal*, 19 (5), 461–77.

Lavie, Dovev and Stewart R. Miller (2008), "Alliance Portfolio Internationalization and Firm Performance," *Organization Science*, 19 (4), 623–46.

Lee, Jongkuk (2011), "The Alignment of Contract Terms for Knowledge-Creating and Knowledge-Appropriating Relationship Portfolios," *Journal of Marketing*, 75 (July), 110–27.

Mallapragada, Girish, Rajdeep Grewal, and Gary Lilien (2012), "User-Generated Open Source Products: Founder's Social Capital and Time to Product Release," *Marketing Science*, 31 (3), 474–92.

McAlister, Leigh, Raji Srinivasan, and MinChung Kim (2007), "Advertising, Research and Development, and Systematic Risk of the Firm," *Journal of Marketing*, 71 (January), 35–48.

Monge, Peter R. and Noshir S. Contractor (2003), *Theories of Communication Networks*. Oxford, UK: Oxford University Press.

Moran, Peter (2005), "Structural Vs. Relational Embeddedness: Social Capital and Managerial Performance," *Strategic Management Journal*, 26 (December), 1129–51.

Mowery, David C., Joanne E. Oxley, and Brian S. Silverman (1996), "Strategic Alliances and Interfirm Knowledge Transfer," *Strategic Management Journal*, 17 (S2), 77–91.

Narasimhan, Om, Surendra Rajiv, and Shantanu Dutta (2006), "Absorptive Capacity in High-Technology Markets: The Competitive Advantage of the Haves," *Marketing Science*, 25 (5), 510–24.

Obstfeld, David (2005), “Social Networks, the Tertius Iungens Orientation, and Involvement in Innovation,” *Administrative Science Quarterly*, 50 (1), 100–30.

Owen-Smith, Jason and Walter W. Powell (2004), “Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community,” *Organization Science*, 15 (1), 5–21.

Pakes, Ariel and Zvi Griliches (1984), “Patents and R&D at the Firm Level: A First Look,” in *R&D, Patents, and Productivity*, Zvi Griliches, ed. Chicago: University of Chicago Press.

Phelps, Corey, Ralph Heidl, and Anu Wadhwa (2012), “Knowledge, Networks, and Knowledge Networks: A Review and Research Agenda,” *Journal of Management*, 38 (4), 1115–66.

Roodman, David (2009), “How to Do Xtabond2: An Introduction to Difference and System GMM in Stata,” *Stata Journal*, 9 (1), 86.

Rowley, Tim, Dean Behrens, and David Krackhardt (2000), “Redundant Governance Structures: An Analysis of Structural and Relational Embeddedness in the Steel and Semiconductor Industries,” *Strategic Management Journal*, 21 (3), 369–86.

Sampson, Rachelle C. (2007), “R&D Alliances & Firm Performance: The Impact of Technological Diversity and Alliance Organization on Innovation,” *Academy of Management Journal*, 50 (2), 364–86.

Schilling, Melissa A. and Corey C. Phelps (2007), “Interfirm Collaboration Networks: The Impact of Large-Scale Network Structure on Firm Innovation,” *Management Science*, 53 (7), 1113–26.

Sorescu, Alina B. and Jelena Spanjol (2008), “Innovation’s Effect on Firm Value and Risk: Insights from Consumer Packaged Goods,” *Journal of Marketing*, 72 (March), 114–32.

Steenkamp, Jan-Benedict E.M. and Eric (Er) Fang (2011), “The Impact of Economic Contractions on the Effectiveness of R&D and Advertising: Evidence from U.S. Companies Spanning Three Decades,” *Marketing Science*, 30 (4), 628–45.

Stephenson, Karen and Marvin Zelen (1989), “Rethinking Centrality: Methods and Examples,” *Social Networks*, 11 (1), 1–37.

Stuart, Toby E. (2000), “Interorganizational Alliances and the Performance of Firms: A Study of Growth and Innovation Rates in a High-Technology Industry,” *Strategic Management Journal*, 21 (8), 791–811.

Subramaniam, Mohan and Mark A. Youndt (2005), “The Influence of Intellectual Capital on the Types of Innovation Capabilities,” *Academy of Management Journal*, 48 (3), 450–63.

Swaminathan, Vanitha and Christine Moorman (2009), “Marketing Alliances, Firm Networks, and Firm Value Creation,” *Journal of Marketing*, 73 (September), 52–69.

Teece, David J. (2007), “Explicating Dynamic Capabilities: The Nature and Microfoundations of (Sustainable) Enterprise Performance,” *Strategic Management Journal*, 28 (13), 1319–50.

Tsai, Wenpin (2001), “Knowledge Transfer in Intraorganizational Networks: Effects of Network Position and Absorptive Capacity on Business Unit Innovation and Performance,” *Academy of Management Journal*, 44 (5), 996.

Tushman, Michael L. and Ralph Katz (1980), “External Communication and Project Performance: An Investigation into the Role of Gatekeepers,” *Management Science*, 26 (11), 1071–85.

Van Beers, Cees and Fardad Zand (2014), “R&D Cooperation, Partner Diversity, and Innovation Performance: An Empirical Analysis,” *Journal of Product Innovation Management*, 31 (2), 292–312.

Van den Bulte, Christophe and Stefan Wuyts (2007), *Social Networks and Marketing. Relevant Knowledge Series*. Cambridge, MA: Marketing Science Institute.

Wuyts, Stefan, Shantanu Dutta, and Stefan Stremersch (2004), “Portfolios of Interfirm Agreements in Technology-Intensive Markets: Consequences for Innovation and Profitability,” *Journal of Marketing*, 68 (April), 88–100.

Xiong, Guiyang and Sundar Bharadwaj (2011), “Social Capital of Young Technology Firms and Their IPO Values: The Complementary Role of Relevant Absorptive Capacity,” *Journal of Marketing*, 75 (November), 87–104.