

Intrafirm Network Structure and Firm Innovation Performance: The Moderating Role of Environmental Uncertainty

Chih-Hung Peng , Ling-Ling Wu, Chih-Ping Wei , and Chun-Mao Chang

Abstract—An interpersonal network within a firm serves as a primary knowledge base for organizational innovation. In this article, we propose that intrafirm network connectivity, which is measured by the transitivity of an intrafirm network, has a nonlinear effect on firm innovation performance. Furthermore, on the basis of the literature on environmental contingency, we propose that two dimensions of environmental uncertainty (i.e., environmental munificence and dynamism) moderate the influence of intrafirm network connectivity on firm innovation performance. To examine our hypotheses, we collect the profiles of firms in the pharmaceutical and biotechnology industries from the COMPU-STAT database and patent data from the United States Patent and Trademark Office database for the period of 1991–2012. Our longitudinal study finds an inverted U-shaped relationship between intrafirm network connectivity and firm innovation performance, and such a relationship is moderated by environmental munificence but not by environmental dynamism.

Index Terms—Environmental uncertainty, intrafirm network, network transitivity, organizational innovation.

I. INTRODUCTION

INNOVATION is “a problem-solving process, in which solutions to economically valuable problems are discovered via search” [1, p. 372]. The internal knowledge necessary for innovation does not generally reside in particular individuals, but in the interpersonal network/collaborative network within their organization (i.e., intrafirm network) [2], [3]. Inside the intrafirm network, knowledge transfer provides individuals with more opportunities for mutual learning and cooperation that encourage the creation of new knowledge and contribute to the

organizational ability to innovate at the same time. Therefore, intrafirm network plays an essential role in organizational innovation [4]–[7].

The first objective of this article is to investigate how the structure/configuration of a whole intrafirm network influences firm innovation performance. Previous intrafirm network research has focused on an ego network and has examined the pattern of ties within a focal node’s immediate set of contacts (i.e., ego network structure), but little work has investigated the pattern of ties among all nodes within an organizational boundary (i.e., whole network structure) [8]. Moreover, most previous studies have explored the relationship between the network structure and the performance of the focal node rather than that of the overall organization. A whole-network approach is needed because the aggregating effect of ego network structures is unnecessarily equal to the effect of a whole network structure [9], [10]. Furthermore, prior research has examined the linear relationship between ego network structure and organizational outcomes [11]–[13]. These prior studies also have obtained inconsistent results; some studies have found that network structure has positive effects, whereas others have found negative ones. Therefore, the effect of intrafirm network structure at the whole network level on firm innovation performance remains unclear. In this article, we focus on one important dimension of network structure,¹ namely, network connectivity (i.e., the extent to which any two nodes stay connected); we measure network connectivity by transitivity among individuals in an intrafirm network [14], [15]. We propose that a nonlinear relationship exists between intrafirm network connectivity at the whole network level and firm innovation performance.

Another gap in the literature taps on the relationship between the external environment and the structure of an intrafirm network. Previous studies have highlighted the effects of environmental contingency on formal organizational structures [16] and have suggested that the most effective organizational structure is the one that fits the contingencies that must be dealt with by the organization [16], [17]. However, the effect of environmental contingency on intrafirm network structure is largely unknown. Given that the research on environmental

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¹Prior literature investigated network structure from different dimensions, including network connectivity, network size, average ties, and average path length. In this article, we focus on network connectivity because, compared with the other dimensions, how network connectivity affects organizational outputs remains unclear.

contingencies emphasizes the interaction between the environment and organizational structure, investigating how and why the interaction between the external environment and intrafirm network structure affects firm innovation performance is theoretically and empirically important. Specifically, the role of the external environment should be included in the study of organizational innovation because such an environment drives the innovation progress of firms and industries [18]. In this case, the second objective of this article is to investigate the moderating effect of the external environmental uncertainty on the relationship between intrafirm network connectivity and firm innovation performance. We further consider two dimensions of environmental uncertainty (i.e., munificence and dynamism) and examine their moderating effects; environmental munificence denotes the degree to which a business environment provides firms with resources that are critical to their operations and with opportunities for growth in an industry [19], [20], whereas environmental dynamism (i.e., turbulence, instability) refers to the extent to which firms encounter the unpredictability and volatility of changes in their business environments [21]–[23]. We focus on these two dimensions because they are directly relevant to resource changes.

To achieve our aforementioned research objectives, we examine the influence of the structure of a patent coinventing network, a type of intrafirm collaborative networks, on firm innovation performance. We collect data on patent coinventing networks within firms in the pharmaceutical and biotechnology industries from 1991 to 2012 because these firms operate in environments with varying levels of uncertainty [24] and because they require innovation to remain competitive in their industries [25], [26]. Our data analysis shows that an inverted U-shaped relationship exists between network connectivity and firm innovation performance, and such a relationship is moderated by environmental munificence but not by environmental dynamism.

This article contributes to the literature in several ways. First, different from the prior works that have focused on the consequence of an ego network structure, we examine the impact of a whole network structure on the overall organization. We also demonstrate a nonlinear performance effect of intrafirm network structure, specifically of network connectivity. Second, we complement the extant literature by investigating the contingency effect of environmental uncertainty on intrafirm network structure. We further investigate different dimensions of environmental uncertainty (i.e., munificence and dynamism) and their contingency effects. Therefore, insights into the performance impact of network structure within a firm have implications for how much managers should value the intrafirm network structure, and the extent to which managers should factor in environmental uncertainty when overseeing or guiding the development of the intrafirm network structure.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

A. Contingency Theory

We draw on contingency theory to provide a theoretical background for developing our hypotheses. Contingency theory posits that no single best way can be used to design, organize, or manage an organization. The extant research on contingency

theory suggests that a structure that fits the contingencies that must be dealt with by the organization is considered the most effective, and such an effective structure enhances organizational performance [17], [27]. Recent studies have examined several contingency variables, including national context and culture [28], [29], organizational size [30], [31], organizational strategy [32], [33], and business environment [34], [35].

Among these contingency variables, environment contingency has received increasingly significant research attention [18], [36]. Most studies on environmental contingency have focused on the interaction between formal organizational structure and environmental variables, e.g., [35], [37], [38], and [39]. For example, Germain *et al.* [37] found that the interaction between organizational structure (formalization and integration) and environmental uncertainty is related to the firm's financial performance. Although the above-mentioned studies have suggested the importance of investigating the interrelationships between formal organizational structure and environmental uncertainty, relatively few studies have examined the interaction between intrafirm network structure and environmental uncertainty.

The following sections are organized as follows. We first describe intrafirm network structure and hypothesize the relationship between intrafirm network structure and organizational performance. Then, on the basis of contingency theory, we hypothesize the moderating effect of environmental uncertainty.

B. Intrafirm Network Structure and Firm Innovation

Intrafirm networks can be constructed by different types of ties (e.g., collaborations, friendships, and colleagueship) within organizational boundaries. Organizational knowledge is distributed in these networks [4]. Therefore, these networks are particularly important for achieving innovation because they affect knowledge transfer and development [4], [5], [40].

In this article, we focus on one specific network structure, namely, network connectivity. Previous studies have identified two types of benefits inherent in network connectivity: information and solidarity benefits [4]–[7]. First, a lowly connected network creates considerable information benefit. This network is composed of individuals who are mutually unconnected. In this network, individuals can gain new or additional information from their indirect contacts because the information is likely to be dissimilar to the information obtained from their direct contacts. In other words, the network allows individuals to access unique information from others whom they are not directly connected to or have not interacted with before [4], [5]. Therefore, a low level of network connectivity provides more nonredundant and diverse information flows than a high level of network connectivity. Previous studies have also demonstrated that the information benefit is positively related to organizational innovation [11], [12]. That is, information diversity within a firm enhances the basis for learning and enables the firm to make new knowledge combination and creation [41].

By contrast, a highly connected network brings in solidarity benefit [6], [13], [42], [43]. In this network, individuals are mutually connected with one another; thus, the development of cooperative norms is promoted [40]. These norms prohibit individuals from engaging in opportunistic behavior and thus

increase the likelihood of future reciprocity and cooperation [13], [42]. Moreover, a highly connected network facilitates the formation of shared routines for information collection and distribution, which enhances the efficiency of knowledge sharing [43]. Therefore, a highly connected network has a larger solidarity benefit than a lowly connected network. Previous studies have shown a positive relationship between such solidarity benefit and organizational innovation [13], that is, solidarity benefit facilitates knowledge sharing and exchange within a firm, which allows the firm to refine existing knowledge and create new knowledge.

Both of these benefits are crucial to organizational innovation and complement each other [44]. In other words, an extremely high or low level of network connectivity will lead to a low level of organizational innovation because one of the benefits is scarce. Therefore, an inverted U-shaped relationship may exist between network connectivity and firm innovation performance. In other words, organizational innovation is optimal at an intermediate level of network connectivity.

In this article, we focus on the connectivity of an intrafirm coinventing network where two inventors are connected if they have a collaborative relationship (i.e., coinventing a patent). Depending on different research purposes, three common measures of connectivity are used in the literature: transitivity, density, and structural holes [13], [14], [45]. The first two measures are often found in the prior studies at the whole network level, whereas the third measure has been used in the prior studies at the ego-network level. In our article, we focus on the whole network level and therefore consider the first two measures. Transitivity is computed by the proportion of closed triangles to the total number of open and closed triangles; a closed triangle is a triad where any two inventors are directly connected to each other, whereas an open triangle is a triad where two inventors are indirectly connected through their mutual contact (i.e., only two connections are observed). Density is computed by the proportion of extant connections to the total number of all possible connections within a network. Transitivity and density capture the different dimensions of network connectivity. In this article, we adopt the transitivity measure because of its two advantages. First, our theoretical arguments (i.e., information and solidarity benefits) focus on the role of mutual contacts, which is also the focus of the transitivity measure. Second, our study includes intrafirm coinventing networks with various sizes. Transitivity measure is therefore more appropriate than density measure because the latter has severe downward bias for large networks [46].

On the basis of the discussion above, we propose that an intermediate level of transitivity in an intrafirm coinventing network will lead to optimal firm innovation performance. When an intrafirm coinventing network is moderately transitive (or closed), such a network enjoys information and solidarity benefits. Specifically, nonredundant and diverse knowledge for innovation is distributed in this network. In addition, this network is also conducive to knowledge sharing and exchange. Both benefits are crucial for organizational innovation. Therefore, we hypothesize the following condition.

Hypothesis 1: Transitivity in an intrafirm coinventing network has an inverted U-shaped relationship with the innovation performance of the firm.

C. Contingency of Environmental Uncertainty

An intermediate level of network transitivity can better support innovation activities. However, the advantages of such transitivity and its interaction with environmental uncertainty remain unclear. As described earlier, we draw on contingency theory to provide a theoretical background. We propose that a firm's innovation performance is attributable to the "match" between its intrafirm network transitivity and its environmental uncertainty. Following the previous studies, e.g., [47] and [48], we focus on two dimensions of environmental uncertainty (munificence and dynamism), which are relevant to resource changes. We further discuss how the effect of network transitivity on firm innovation performance is contingent on environmental munificence and dynamism.

D. Environmental Munificence

Environmental munificence denotes the scarcity or abundance of critical resources needed by firms operating within an environment [19], [20]. In a highly munificent environment, abundant resources (e.g., high market demand and industry sales growth) are available to organizations [20], that is, critical resources are widely available to firms in munificent environments. Such resource abundance provides conducive conditions for firms to explore and develop innovative technologies, products, or services [19], [21].

Previous studies have examined the relationship between environmental munificence and organizational strategy. For example, Lumpkin and Dess [49] examined the contingent effect of environmental munificence on the relationship between a firm's proactive orientation and its performance. Proactive firms are interested in experimenting and introducing new products and technologies for seeking market opportunities [50], [51]. Lumpkin and Dess [49] found that proactive firms perform better in munificent environments than in hostile ones (i.e., less munificent environments) because the former allows these firms to experiment with new strategies and innovative products.

According to the Lumpkin and Dess's findings, we can reasonably expect that in a munificent environment, a firm must possess an intrafirm network structure that allows it to be proactive in responding to the abundance of accessible resources. A lowly transitive network is likely proactive-oriented because information diversity within this network is high. Such high information diversity enhances the potential to generate new products, services, technologies, or processes/systems, all of which can help firms compete for new external resources. Therefore, an optimal network transitivity should shift from an intermediate level toward a lower level to elicit the highest level of innovation, that is, in a higher environmental munificence, a lower level of network transitivity is effective and beneficial for organizational innovation. Therefore, we propose that environmental munificence moderates the relationship between

intrafirm network transitivity and firm innovation performance as stated in Hypothesis 2.

Hypothesis 2: Environmental munificence moderates the inverted U-shaped relationship between the degree of transitivity in an intrafirm coinventing network and the innovation performance of a firm. The degree of transitivity in the intrafirm coinventing network is negatively related to the innovation performance of the firm in a highly munificent environment, whereas the inverted U-shape is retained in a lowly munificent environment.

E. Environmental Dynamism

Environmental dynamism indicates turbulence and instability in a business environment. Specifically, environmental dynamism involves variations in technologies, product demands, material supplies, or customer preferences [18], [52]. When environmental dynamism increases, firms encounter increased difficulty in predicting assets and capabilities needed in their business environments. That is, firms have difficulty in sustaining their competitive advantages. Therefore, in minimizing these threats, the need for organizational learning is magnified.

We argue that, in a dynamic environment, a moderately transitive network is an effective structure for firm innovation. In a dynamic environment, a firm increases its need for organizational learning [23]. As described earlier, a moderately transitive network facilitates organizational learning because this network enjoys both information and solidarity benefits. Because the need for organizational learning can be fulfilled by a moderately transitive network, a “match” between a dynamic environment and a moderately transitive network occurs. This match further enhances the benefits of organizational learning (e.g., sense events and trends in a dynamic environment), thereby creating new competitive advantages [53], [54]. In conclusion, the effect of an intermediate level of network transitivity is enhanced in a more dynamic environment. In other words, the inverted U-shaped relationship between intra-firm network transitivity and firm innovation performance becomes more pronounced in a dynamic environment than in a stable environment. We hypothesize the following.

Hypothesis 3: Environmental dynamism moderates the inverted U-shaped relationship between the degree of transitivity in an intrafirm coinventing network and the innovation performance of a firm. The inverted U-shape is more pronounced in a high environmental dynamism condition than in a low environmental dynamism condition.

III. METHODOLOGY

A. Data

To examine our hypotheses, we opted to conduct our study in four pharmaceutical and biotechnology industries, namely, the medicinal chemicals and botanical products industry (Standard Industrial Classification (SIC): 2833), pharmaceutical preparations industry (SIC: 2834), diagnostic substances industry (SIC: 2835), and biological products industry (SIC: 2836). We selected the four industries due to several reasons. First, environmental uncertainty in these industries varies regularly because of the frequent changes in user requirements and regulations [55]. For example, firms in these industries typically have difficulties in predicting markets due to the increasing number of rules relating

to the effectiveness and safety of drugs and medical devices as well as the increasing number of competitors entering the market with generic drugs and competitive medical devices. Second, firms in the pharmaceutical and biotechnology industries encourage patenting activities and tend to patent all possible knowledge because these firms can receive substantial revenue streams from their patents until these patents expire [56].

We mainly collected our data from two sources. First, we used the COMPUSTAT database to extract a list of company names in the four selected industries. We eventually obtained a list of 744 active public U.S. companies. We collected the profiles of these sample companies from the same database, including their sales, R&D expenditure, and number of employees.

Second, we matched the company names to patent assignees and then downloaded patent data from the United States Patent and Trademark Office (USPTO) database for the period of 1991–2012.² We then used the Delphion database to solve the variations in the names of patent assignees. When a firm applies for patents, it may use different name variants as assignee names. For example, the German drug company Bayer used Bayer AG, Bayer Aktiengesellschaft, and Bayer Corporation as assignee names for its various patents. Ignoring these name variants would make the patents retrieved for a firm appear incomplete and biased. By using the Delphion database, we obtained all possible names used by the focal firm and then manually examined and identified its name variants. We found that 329 firms have patent data during the study period, and we eventually obtained 2613 firm-year observations.³ Each patent included several pieces of information, such as application date, issue date, assignee(s), inventor(s), patent classes, and references cited.

After the patent assignee names were identified, we addressed the variations in the names of patent inventors, who can also use different name variants. For example, an inventor may opt to use his or her first and middle initials when filing some patents, but use his or her complete first and middle names in other patents. Ignoring the variants in the patent inventor names would damage the quality of the resultant intrafirm coinventing networks for the sample firms. Following other studies [58], [59], we used a machine learning approach to implement a name-matching algorithm for inventor name disambiguation and used it to create coinventing networks from our data.

B. Measures

1) *Dependent Variable*: Recent studies have measured firm innovation performance on the basis of patent quality [60]–[62]. We measured *firm innovation performance* by using the sum of forward citations received by successful (i.e., granted) patent applications of firm i in year $t + 1$. A five-year window from the patent application date was selected in computing the number of forward citations [61]. Following previous studies [13], we used the patent application date to assign a granted patent to the

²With respect to the data period, we followed the recommendations of Hegde [57] in collecting patent data from 1991 onward because the Omnibus Reconciliation Act of 1990 has a large impact on USPTO's processing of patent applications.

³We obtained unbalanced panel data due to some missing observations.

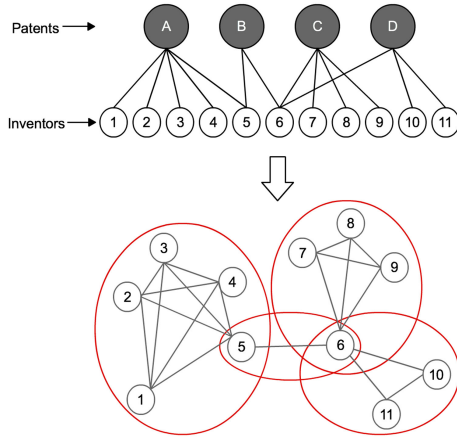


Fig. 1. Intrafirm coinventing network.

particular year in which this patent was originally applied. For example, if a firm applied for a patent in 2006 and this patent was granted in 2008, then we considered this patent to be a patent in 2006. The number of forward citations received by a patent indicates the extent to which the target patent contributes to future knowledge development. A patent with more forward citations generally has greater economic value than a patent with fewer forward citations [63]. Therefore, the total number of forward citations received by a patent can serve as a proxy for calculating firm innovation performance. We also used a one-year lag between our dependent variable (year $t + 1$) and other variables (i.e., independent and control variables, year t) to address concerns on reverse causality.

2) *Independent Variable. Transitivity of an Intrafirm Network*: We used the successful patent applications of a firm to construct an intrafirm coinventing network for the focal firm. In this network, an inventor is represented by a node and a coinventing relation is represented by a link. A link exists between two inventors if they have coinvented a patent. As shown in Fig. 1, a target firm has four patents (patents A, B, C, and D), and patent A is assumed to be invented by inventors 1, 2, 3, 4, and 5. In this case, each pair of patent A inventors is connected by a link in the coinventing network of the focal firm. We measured network transitivity in a five-year moving window. For example, we used the intrafirm coinventing network constructed from the patents that the focal firm applied from years $t - 4$ to t (e.g., 2001–2005) to measure the network transitivity for year t (e.g., 2005).

We measured *Network Transitivity* on the basis of the proportion of the directly interlinked collaborators of a focal inventor [64], [65]. Specifically, we calculated network transitivity as

$$\text{Transitivity} = \frac{3 \times (\# \text{ triangles in a network})}{(\# \text{ connected triples})}$$

where a “triangle” is a trio of interlinked inventors and a “connected triple” is a single inventor that is linked to two others. The coefficient takes a value between 0 and 1. As shown in Fig. 1, network transitivity takes a value of 0.75 because the network includes 15 triangles and 60 connected triples. A high

value indicates that the inventors in a coinventing network cluster together.

3) *Moderators. Environmental Uncertainty*: Following prior studies, e.g., [19], [22], [66], and [67], we examined two dimensions of environmental uncertainty: dynamism and munificence. *Dynamism* refers to the volatility of the changes in a business environment. Following Keats and Hitt [21], we selected sales volatility and operating income volatility as two indicators of environmental dynamism. We measured sales volatility in two steps. First, we regressed the natural log of the total sales in a particular four-digit SIC industry against an index variable of year over a five-year period. Equation (1) shows the regression. Second, we obtained the antilog of the standard error of the regression coefficient (i.e., b_1) as a measure of sales volatility. We calculated operating income volatility in a similar fashion. We aggregated the two volatility measures into one measure by using a weighted average in which the values of the factor loadings from Keats and Hitt [21] were used as weights. A high average value of the two indicators indicates that a business environment is highly dynamic. A robustness check indicates that the results obtained using the simple and weighted averages of two volatility measures are consistent with each other. We will discuss this robustness check further in the later part of this article

$$y = b_0 + b_1 t + \varepsilon \quad (1)$$

where y is the natural log of the total sales in year t , t is the index variable of year, and ε is the residual.

Munificence refers to growth opportunities in an industry [19]. Following Keats and Hitt [21], we measured the environmental munificence of an industry by using two indicators: the five-year average growths in net sales and operating income. We also measured the five-year sales growth in two steps. First, we regressed the natural log of total sales in a four-digit SIC industry against an index variable of year over a five-year period. Second, we considered the antilog of the regression coefficient as a measure of five-year sales growth. We computed operating income growth in a similar fashion. We converted the two growth measures into one by using a weighted average, which used the values of the factor loadings from Keats and Hitt [21] as weights. A high average value of the two indicators indicates that a business environment is highly munificent. Similarly, the results obtained using the simple and weighted averages of two growth measures are consistent with each other. This robustness check will be further discussed in the later part of this article.

C. Control Variables

We controlled for possible confounding effects by including relevant control variables in our empirical study.⁴ First, we included *firm R&D intensity* to control for absorptive capacity

⁴We did not control for *firm presample patents*, which refer to the sum of successful patent applications filed by a firm in the five years prior to its entry in the sample. The correlation between *firm presample patents* and *intrafirm network size* is extremely strong (0.93). Given that *firm presample patents* and *intrafirm network size* represent the patenting ability of a firm, we excluded the former and included the latter in our models. The results with and without *firm presample patents* are consistent with each other.

at the firm level [41], [68]. We computed R&D intensity by dividing R&D expenditure by the total sales of firm i in year t [69]. Second, we included *firm current ratio* to control for the availability of slack resources [70]. We then measured this ratio by dividing the assets of firm i by its liabilities in year t . Third, we measured *firm age* by using the number of years since the firm was founded. We included firm age in the model because those firms that have been in existence for a longer time generally have greater technological capabilities [71]. Fourth, we included *firm size* because larger firms tend to have more innovation outputs than smaller firms. We measured firm size by using the number of employees (thousands) in a focal firm.

We also included the control variables related to the intrafirm network and knowledge development of firms. First, we measured the size of an intrafirm network by counting the number of inventors in the past five years (i.e., from years $t - 4$ to t) (*intrafirm network size*). Second, we measured network density (*intrafirm network density*) by dividing the number of actual links by the number of all possible links within the network [72].⁵

Third, given the important role of knowledge diversity in ensuring firm innovation performance, we controlled for *technological diversity* and *R&D location diversity*. We measured technological diversity by using the Blau index [73], which is defined as

$$\text{Technological Diversity}_{it} = 1 - \sum_{j=1}^J \left(\frac{N_{jit}}{N_{it}} \right)^2$$

where N_{it} is the number of successful patent applications filed by firm i in the past five years (i.e., from years $t - 4$ to t) and N_{jit} is the number of successful patent applications in technology class j in the five-year patent stock of firm i . The value of diversity ranges from 0 to 1, where a value close to 0 indicates a low level of technological diversity, whereas a value close to 1 indicates a high level of technological diversity.

Similarly, given the importance of the diversity of geographic R&D locations in ensuring firm innovation performance [61], [74], we used the Blau index to measure R&D location diversity as follows:

$$\text{Location Diversity}_{it} = 1 - \sum_{j=1}^J \left(\frac{L_{jit}}{L_{it}} \right)^2$$

where L_{it} is the number of inventors in firm i in the past five years and L_{jit} is the number of inventors at city j in the past five years.⁶

Grigoriou and Rothaermel [75] found a relationship between internal knowledge properties and knowledge development. In

turn, we controlled for two internal knowledge properties: the level of knowledge coordination cost and the potential for knowledge creation. We measured coordination cost by calculating the average number of collaboration ties of inventors (*average tie per inventor*), and we measured the potential for knowledge creation by computing the average distance between any two inventors in an intrafirm network (*average path length*). We also included four-digit SIC dummies in our models to control for industry-specific effects. Year dummies were also included to control for economy- or market-wide shocks that vary over time.

D. Model Specification

We used firm innovation performance (i.e., five-year count of forward citations received by the successful patent applications filed by firm i in year $t + 1$) as our dependent variable. Given that this variable is a count measure, using a Poisson regression model was reasonable. However, this model has a strong assumption that the dependent variable has an equal mean and variance, but this assumption is often violated in patent data [76]. The variance in patent data typically exceeds its mean, thereby indicating the presence of overdispersion. Although the estimated coefficients are consistent under this phenomenon, their standard errors are underestimated, thereby leading to spuriously high levels of significance [77]. Therefore, to test our hypotheses, we used a negative binomial model that can address the overdispersion issue. Given the panel nature of our data, we considered adopting either a random-effect or a fixed-effect negative binomial regression model to examine firm innovation performance. The results of the Hausman test ($\chi^2 = 426.15$, $p < 0.001$) suggested that a fixed-effect model is more appropriate for our data.

E. Data Analysis

Table I lists the means, standard deviations, minimum values, maximum values, and correlations of the variables in our analysis. Most correlations were below 0.70, but two correlations were above the threshold. First, the correlation between *firm size* and *intrafirm network size* was high (0.76). This result indicated that larger firms have larger intrafirm coinventing networks than smaller firms. Second, *intrafirm network size* and *average path length* were also highly correlated (0.78), indicating that larger intrafirm coinventing networks have longer distances between inventors than smaller intrafirm coinventing networks. We computed the variance inflation factor scores for all independent variables and found that all scores were below the rule-of-thumb value of 10 [78]. These results suggested that multicollinearity may not be a concern.

Table II lists the results of our hypothesis test. Hypothesis 1 suggested an inverted U-shaped relationship between intrafirm network transitivity and firm innovation performance. Previous studies have proposed a three-step procedure to test such a relationship [79], [80]. First, the coefficient of the squared term for *network transitivity* needs to be significant and negative. Model 3 in Table II shows that the squared term of *network transitivity* was negative and significantly related to *firm innovation performance* ($\beta = -1.323$, $p < 0.05$). Second, the slopes

⁵As previously described, density and transitivity measures capture different dimensions of network connectivity. We controlled for network density to avoid the issue of omitted variable because of its reported relationship with the organizational performance [12].

⁶When computing R&D location diversity, we gave the same weight to all R&D locations. However, some R&D locations may be more important than the others, that is, the weights should be different. Therefore, future research should take this difference into its consideration when examining the relationship between R&D location diversity and firm innovation performance.

TABLE I
DESCRIPTIVE STATISTICS AND CORRELATIONS

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Firm Innovation Performance	1.00													
2. Network Transitivity	-0.03	1.00												
3. Munificence	0.09	-0.04	1.00											
4. Dynamism	-0.07	-0.05	-0.33	1.00										
5. Firm R&D Intensity	-0.01	0.02	0.00	-0.01	1.00									
6. Firm Current Ratio	-0.07	-0.02	-0.02	-0.02	0.01	1.00								
7. Firm Age	0.35	0.03	0.10	-0.09	-0.02	-0.18	1.00							
8. Firm Size	0.39	0.02	0.09	-0.09	-0.02	-0.14	0.66	1.00						
9. Intrafirm Network Size	0.48	-0.01	0.08	-0.09	-0.02	-0.13	0.55	0.76	1.00					
10. Intrafirm Network Density	-0.22	0.15	-0.01	0.01	0.01	0.06	-0.26	-0.26	-0.32	1.00				
11. Technological Diversity	0.25	0.15	-0.03	0.01	0.01	-0.09	0.27	0.30	0.36	-0.58	1.00			
12. Location Diversity	0.07	0.33	0.02	-0.13	0.03	-0.06	0.22	0.29	0.27	-0.24	0.35	1.00		
13. Average Tie Per Inventor	0.06	0.18	0.01	-0.05	0.00	0.00	0.00	0.04	0.20	-0.15	0.26	0.16	1.00	
14. Average Path Length	0.48	0.03	0.04	-0.07	-0.01	-0.12	0.45	0.56	0.78	-0.41	0.48	0.30	0.33	1.00
Mean	8.61	0.64	1.07	1.01	30.38	6.95	20.17	4.30	74.51	0.33	0.46	0.50	3.70	1.72
Standard Deviation	34.10	0.31	0.03	0.01	464.52	10.56	28.30	15.21	202.43	0.30	0.29	0.31	3.84	1.10
Min	0.00	0.00	0.99	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	839.00	1.00	1.15	1.03	25684.40	318.82	232.00	122.20	1864.00	1.00	0.95	0.99	40.45	11.60

TABLE II
RESULTS OBTAINED BY FIXED-EFFECT NEGATIVE BINOMIAL MODEL (DV:
FIRM INNOVATION PERFORMANCE)

	Model 1	Model 2	Model 3	Model 4
Firm R&D Intensity	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Firm Current Ratio	0.007** (0.003)	0.007** (0.003)	0.006** (0.003)	0.006* (0.003)
Firm Age	-0.002 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Firm Size	-0.005* (0.003)	-0.004* (0.003)	-0.004 (0.003)	-0.004* (0.003)
Intrafirm Network Size	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Intrafirm Network Density	-1.203*** (0.220)	-1.055*** (0.217)	-0.907*** (0.228)	-0.989*** (0.232)
Technological Diversity	0.918*** (0.184)	1.084*** (0.190)	1.042*** (0.191)	0.997*** (0.193)
Location Diversity	-0.254* (0.150)	-0.161 (0.152)	-0.178 (0.153)	-0.208 (0.154)
Average Tie Per Inventor	-0.000 (0.008)	0.001 (0.008)	-0.002 (0.008)	-0.002 (0.008)
Average Path Length	0.157*** (0.027)	0.152*** (0.028)	0.137*** (0.029)	0.136*** (0.029)
Munificence		-0.952 (1.077)	-0.821 (1.079)	13.222** (5.614)
Dynamism		-1.386 (6.212)	-2.064 (6.192)	15.594 (19.150)
Network Transitivity		-0.540*** (0.157)	0.884 (0.585)	104.069 (64.508)
Network Transitivity ²			-1.323** (0.520)	-74.914 (56.702)
Munificence × Network Transitivity				-52.889*** (17.594)
Munificence × Network Transitivity ²				44.561*** (14.747)
Dynamism × Network Transitivity				-45.898 (61.708)
Dynamism × Network Transitivity ²				25.543 (53.097)
Constant	-0.644** (0.305)	1.988 (6.801)	2.273 (6.784)	-30.626 (19.666)
Observations	2613	2613	2613	2613
Log likelihood	-4,703.53	-4,697.41	-4,694.11	-4,688.27

Year and industry dummy variables are included; standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

at both ends of the data range must move in different directions. The range for *network transitivity* is between 0 and 1, and the slopes at the values of 0 and 1 were positive ($\beta = 0.884$, $p = 0.1$) and negative ($\beta = -1.762$, $p < 0.01$), respectively. Third,

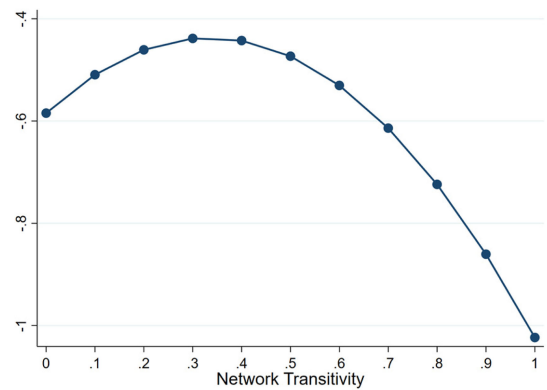
Log of conditional mean of *Firm Innovation Performance*

Fig. 2. Nonlinear relationship between network transitivity and firm innovation performance.

the turning point needs to be located within the data range. The calculated turning point was 0.3, which is within the data range. This three-step procedure confirms that an inverted U-shaped relationship exists between network transitivity and firm innovation performance. In Fig. 2, we plotted the relationship between network transitivity and firm innovation performance on the basis of Model 3 while holding the other variables at their mean values. We selected three levels of network transitivity [i.e., turning point (0.3) and turning points below (0) and above (0.6) one standard deviation of network transitivity] to illustrate this inverted U-shaped relationship. Fig. 2 shows that, when network transitivity increases from 0 to 0.3, the difference in the logs of expected counts of firm innovation performance increases by 0.2. Meanwhile, when network transitivity increases from 0.3 to 0.6, the difference decreases by 0.1. Fig. 2 shows this inverted U-shaped relationship. Therefore, Hypothesis 1 was empirically supported.

Hypothesis 2 suggested that environmental munificence moderates the inverted U-shaped relationship between network transitivity and firm innovation performance. Specifically, such a relationship is retained in a lowly munificent environment, and

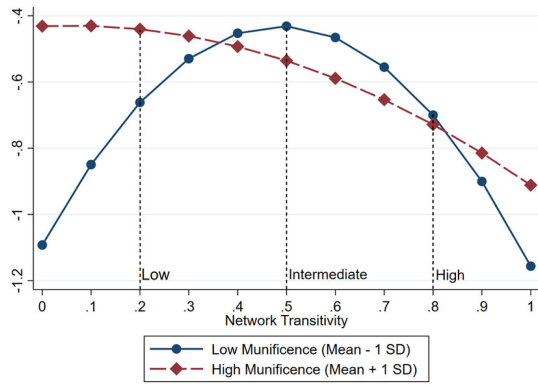
Log of conditional mean of *Firm Innovation Performance*

Fig. 3. Moderating effect of environmental munificence.

the degree of transitivity in an intrafirm coinventing network is negatively related to the innovation performance of the firm in a highly munificent environment. Model 4 of Table II shows that the interaction effect of *munificence* and the squared term of *network transitivity* on *firm innovation performance* were significant ($\beta = 44.561$, $p < 0.01$). To further examine this moderating effect, we plotted the relationship between network transitivity and firm innovation performance on the basis of Model 4. We divided environmental munificence into low (one standard deviation below the mean) and high (one standard deviation above the mean) groups. We treated the low environmental munificence condition as a baseline group and then extracted the three levels of *network transitivity*, namely, low (one standard deviation below the turning point of the regression curve), intermediate (the turning point), and high (one standard deviation above the turning point), from the regression curve for this group [79], [81]. We also examined the simple slopes of the regression curve at the three levels. As shown in Fig. 3, the turning point is 0.5 at a low level of environmental munificence, whereas the simple slope of the regression curve is significantly positive at a low level of *network transitivity* ($\beta_{\text{Low}} = 1.60$, $p < 0.05$), not significantly different from zero at the intermediate level ($\beta_{\text{Intermediate}} = -0.06$, $p > .10$), and significantly negative at the high level ($\beta_{\text{High}} = -1.73$, $p < 0.001$). By contrast, at a high level of environmental munificence, the simple slopes of the regression curve were all negative at the low, intermediate, and high levels ($\beta_{\text{Low}} = -1.54$, $p > 0.10$; $\beta_{\text{Intermediate}} = -0.48$, $p < 0.01$; $\beta_{\text{High}} = -0.81$, $p < 0.05$). These simple slope tests suggested that an increase in environmental munificence reduces the positive effect and attenuates the negative effect of network transitivity on firm innovation performance. That is, the inverted U-shaped relationship is flatter at a high level than at a low level of environmental munificence.

Fig. 3 shows that, under the condition of low environmental munificence, when network transitivity increases from the low level to the intermediate level and from the intermediate level to the high level, the differences in logs of the expected counts of firm innovation performance increase by 0.3 and decrease by 0.3,

TABLE III
RESULTS OBTAINED BY UNCONDITIONAL FIXED-EFFECT NEGATIVE BINOMIAL MODELS (MODELS 5 AND 6) AND AN ALTERNATIVE MEASURE FOR ENVIRONMENTAL UNCERTAINTY (MODELS 7 AND 8)

	Model 5	Model 6	Model 7	Model 8
Firm R&D Intensity	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Firm Current Ratio	0.009* (0.005)	0.009* (0.005)	0.006** (0.003)	0.006* (0.003)
Firm Age	0.000 (0.000)	0.000 (0.000)	-0.001 (0.001)	-0.001 (0.001)
Firm Size	-0.010 (0.006)	-0.010 (0.006)	-0.004 (0.003)	-0.004* (0.003)
Intrafirm Network Size	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Intrafirm Network Density	-0.854*** (0.292)	-0.800*** (0.294)	-0.906*** (0.228)	-0.982*** (0.231)
Technological Diversity	1.036*** (0.269)	1.044*** (0.269)	1.042*** (0.191)	1.000*** (0.193)
Location Diversity	-0.485** (0.227)	-0.449** (0.228)	-0.179 (0.153)	-0.208 (0.154)
Average Tie Per Inventor	-0.005 (0.011)	-0.006 (0.011)	-0.002 (0.008)	-0.002 (0.008)
Average Path Length	0.151*** (0.058)	0.151*** (0.058)	0.137*** (0.029)	0.136*** (0.029)
Munificence	-2.840** (1.336)	6.561 (5.508)	-0.870 (1.078)	13.250** (5.574)
Dynamism	-12.510 (7.852)	4.169 (22.208)	-2.055 (5.263)	10.357 (16.395)
Network Transitivity	0.886 (0.741)	87.486 (77.788)	0.886 (0.585)	86.750 (56.468)
Network Transitivity ²	-1.217* (0.678)	-63.282 (70.205)	-1.325** (0.520)	-61.820 (49.752)***
Munificence × Network Transitivity		-44.365** (18.244)		-52.601*** (17.491)
Munificence × Network Transitivity ²		41.794*** (16.111)		44.005** (16.680)
Dynamism × Network Transitivity		-38.442 (73.548)		-28.979 (52.835)
Dynamism × Network Transitivity ²		16.989 (65.398)		13.115 (45.467)
Constant	15.644* (8.414)	-11.466 (23.168)	2.325 (5.909)	-25.385 (17.176)
Observations	3031	3031	2613	2613
Log likelihood	-5,838.87	-5,834.79	-4,694.07	-4,688.39

Year and industry dummy variables are included; standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

respectively. Meanwhile, under the condition of high environmental munificence, when network transitivity increases from the low level to the intermediate level and from the intermediate level to the high level, the differences in logs of the expected counts of firm innovation performance decrease by 0.1 and 0.2, respectively. Therefore, Hypothesis 2 was supported.

Hypothesis 3 proposed that environmental dynamism positively moderate the inverted U-shaped relationship between network transitivity and firm innovation performance. Specifically, the inverted U-shape relationship at a high level of environmental dynamism is more pronounced than that at a low level of environmental dynamism. Model 4 of Table II shows that the interaction effect of *dynamism* and the squared term of *network transitivity* on *firm innovation performance* are not significant ($\beta = 25.543$, $p > 0.10$). Therefore, Hypothesis 3 was not supported.

F. Robustness Checks

We conducted several robustness tests. First, we checked whether our results were robust using an alternative model specification. We used a fixed-effect negative binomial model that is

based on a conditional maximum-likelihood estimation procedure [76]. Allison and Waterman [82] proposed an unconditional procedure by using dummy variables to represent fixed effects, thereby effectively controlling for all time-invariant covariates. We obtained consistent results by using an unconditional procedure as shown in Models 5 and 6 of Table III. Second, we checked whether our results were robust using alternative measures of environmental uncertainty: munificence and dynamism. For each dimension of environmental uncertainty, we followed Keats and Hitt [21] to aggregate multiple measurement items into one measure by using a weighted average. In this robustness check, we used a simple average of the measurement items. We found that the moderating effects of the dimensions of environmental uncertainty on the relationship between *network transitivity* and *firm innovation performance* (Models 7 and 8 in Table III) were consistent with the results reported earlier.

IV. CONCLUSION

A. Discussion of Major Findings

In this article, we proposed that intrafirm network transitivity has a nonlinear effect on firm innovation performance. Our analysis of patent coinventing networks provided support to the inverted U-shaped relationship between intrafirm network transitivity and firm innovation performance. Specifically, Fig. 2 showed that patent coinventing networks with an intermediate level of transitivity demonstrated greater innovation performance than those with a low or high level of transitivity because the former networks enjoy information and solidarity benefits.

Drawing on the literature on environmental contingency, we also proposed that the inverted-U shaped relationship between intrafirm network transitivity and firm innovation performance was contingent on the dimensions of environmental uncertainty. We found that environmental munificence moderates this inverted-U shaped relationship. Fig. 3 showed that, when environmental munificence increases (from a low level to a high level), the optimal level of network transitivity shifts to the left. Specifically, a lowly transitive network was effective in developing organizational innovation in a highly munificent environment because such network has the potential to fully utilize the resources and opportunities provided by this environment.

However, we found that environmental dynamism showed no significant moderating effect on the relationship between intrafirm network transitivity and firm innovation performance. One possible reason is that, in contrast to the opportunities offered by environmental munificence, environmental dynamism implies threats to organizations. When organizations encounter environmental threats, they generally seek stability in their respective organizational structures [83], which in turn results in a threat-rigidity response that allows these firms to maintain the status quo operations. As described earlier, an intermediate level of network transitivity supports innovation activities better than the other levels. Therefore, the advantages from such transitivity are likely to be retained in high- and low-dynamic environments. In other words, an intermediate transitive network may remain effective when environmental dynamism changes.

B. Theoretical Contributions

Our article complements the existing literature by empirically verifying a conceptual framework linking intrafirm network structure/configuration and firm innovation performance. Prior studies have examined and found the curvilinear effect of intrafirm network connectivity at the ego-network level on organizational outputs [84], [85], but the linear effect at the whole-network level [45], [86]. However, our study finds an inverted U-shaped relationship between intrafirm network connectivity at the whole-network level and firm innovation performance. Our finding alters the extant understanding of the effect of intrafirm network connectivity at the whole-network level. Furthermore, we advocated an appropriate measure of network connectivity at the whole-network level. We measured network connectivity by transitivity of a whole network. This measure differs from those of previous studies, most of which measure network connectivity by network density [45], [86]. The use of this measure has one critical advantage: bias reduction for large network size. In other words, transitivity measure is better than density measure because the latter has severe downward bias for large networks [46]. Therefore, future studies should consider using transitivity measures when they are interested in examining the impact of connectivity of large networks (e.g., patent coinventing networks).

Another major theoretical contribution of this article relates to the integration of contingency theory with the literature on intrafirm network structure. Prior literature has examined the environmental contingency on formal organizational structures, e.g., [37] and [38]. However, intrafirm network structure (more specifically, collaborative network structure) is not one of the formal organizational structures. Therefore, our article extends the knowledge frontier of contingency theory by empirically investigating contingency of environmental uncertainty on the relationship between intrafirm network structure and firm innovation performance. We further contribute to this research stream by examining two salient dimensions of environmental uncertainty. Previous studies have suggested that examining multiple dimensions of environmental uncertainty can enrich our understanding of environmental contingency [19], [21], [47], [48]. Therefore, by categorizing uncertainty into munificence and dynamism, we can further understand the contingent effect of environmental uncertainty on this relationship.

C. Managerial Implications

Our empirical findings demonstrate that the intrafirm coinventing network can significantly affect firm innovation performance. Specifically, an intermediate transitive network performs better than networks with a low or high level of transitivity. Therefore, we propose some potential strategies for managers to maintain an intermediate level of network transitivity.

To increase network transitivity from a low to an intermediate level, managers can encourage inventors to reach out to their peers outside their original subnetworks. For example, collaborations that involve cross-functional teams or cross-group collaborations can connect inventors from different groups, thereby

increasing the transitivity of the coinventing network. In addition, managers can move productive inventors from their existing teams to new groups to augment the transitivity of an intrafirm coinventing network. Alternatively, managers can cultivate an apprenticeship practice or culture for R&D in which each junior member works closely with at least one senior member (i.e., experienced inventor) on some innovation projects. With this arrangement, junior members will not only tap into the knowledge and experiences of senior members but also connect to their networks, thereby increasing the transitivity of the coinventing network of a firm.

By contrast, managers can adopt some approaches to help reduce the level of transitivity of an intrafirm coinventing network. The most effective of these approaches is to invite non-R&D employees to participate in innovation development. For example, the 3M Company encourages non-R&D employees to spend 15% of their time exploring breakthrough innovations. Such practices can effectively expand the size of an intrafirm coinventing network and thus reduce network transitivity. Given that many non-R&D employees (e.g., marketing professionals) have opportunities to directly interact with customers, they may possess more unique knowledge on customer preferences (e.g., the pros and cons of products) than R&D members. Such customer-centric knowledge promotes the development of new technologies, products, or services. Accordingly, non-R&D employees who participate in innovation developments not only decrease network transitivity but also improve innovation quality.

In overseeing the level of transitivity in coinventing networks, managers should consider environmental factors when investing in either increasing or decreasing network transitivity. We find that such investments can produce a large range of benefits in certain environmental conditions. For example, a low level of network transitivity is more beneficial to firm innovation performance in a highly munificent environment than in a lowly munificent one. Thus, managers should focus not only on network transitivity but also on contextual factors when overseeing their intrafirm networks.

D. Limitations and Future Research

In this article, we acknowledged a few limitations that can create avenues for future research. First, we examined our hypotheses by using pharmaceutical and biotechnology industries. Although we have selected several industries to test our hypotheses, future research can focus on other industries (e.g., information and communications technology industries) to verify our findings and enhance their generalizability.

Second, we used patents as a proxy for firm innovation. Specifically, we measured firm innovation performance by using the number of forward citations received by the granted patents filed by the focal firm. Patents, which are considered outcomes of innovation, are widely deemed as appropriate proxies of firm innovation. However, other innovations, such as product designs, production procedures, or creative customer services, may not be reflected in patents even if they can substantially contribute to firm performance. Therefore, future research can use other

possible measures (e.g., survey items) to complement our patent measure.

Third, our findings were based on a single type of intrafirm network. We relied on inventor collaboration ties to construct intrafirm networks because copatenting has been demonstrated to include critical knowledge transfer [10], [75]. However, other ties, such as friendships or information seeking relationships, also involve knowledge transfer. Therefore, future research can benefit from investigating other types of relationships apart from copatenting relationships. In this way, they can obtain a highly comprehensive understanding of the influence of intrafirm network structure on firm innovation performance.

Fourth, we assessed the moderating effect of environmental uncertainty on the relationship between intrafirm network structure and firm innovation performance. Previous studies have suggested the existence of different types of uncertainties [34], [87]; some of these types are unique and internal to single firms (e.g., technological uncertainty), whereas others are external and shared across firms in their respective industries (e.g., environmental uncertainty). Therefore, future research can investigate the moderating effect of different types of uncertainties (including technological and environmental) on the effect of intrafirm network structure on firm innovation performance. Moreover, an intrafirm network and an interfirm alliance network contribute to different types of knowledge transfer. Therefore, future research can examine and compare the moderating effect of environmental uncertainty on the effects of both network structures on firm innovation performance. The findings from such comparison can enrich our understanding of the ways to exploit the two types of networks for improving firm innovation performance.

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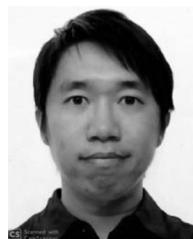
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