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Employee co-invention network dynamics and firm exploratory innovation: the moderation of employee co-invention network centralization and knowledge-employee network equilibrium

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Abstract
Drawing on a dynamic approach, increasing research investigates network dynamics at the inter-firm level in recent years. However, little is known about intra-firm employee network dynamics and their consequences for firm exploratory innovation. This paper addresses the gap by focusing on employee co-invention network dynamics conceptualized as employee turnover and across-team movement. Based on the knowledge-based view and transactive memory system theory, this research elaborates on the dual mechanism of employee co-invention network dynamics and proposes an inverted U-shaped relationship between employee co-invention network dynamics and firm exploratory innovation. Furthermore, employees and their innovation are structurally embedded in the intra-firm networks. This paper investigates the moderation effect of intra-firm network structures. First, employee co-invention network centralization, indicating a core-periphery co-invention structure among employees, may negatively moderate the inverted U-shaped relationship. Second, knowledge-employee network equilibrium, indicating an evenly- and broadly- distributed knowledge structure among employees, may positively moderate the inverted U-shaped relationship. Based on patent data of 76 high-tech firms over 31 years from 1990 to 2020, this paper develops novel quantitative measures and conducts panel regression analysis. Results support all the above predictions.

Keywords Employee co-invention network dynamics · Firm exploratory innovation · Employee co-invention network centralization · Knowledge-employee network equilibrium

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Introduction

Increasing research investigates network dynamics (or the opposite concepts like network stability and network inertial) and their consequences for exploratory innovation in recent years. Research drawing on the knowledge-based view (e.g., Kumar & Zaheer, 2019), social capital (e.g., Yan & Guan, 2018), and network inertial (e.g., Wang & Yang, 2019) has confirmed the positive mechanisms of network dynamics. Meanwhile, research drawing on absorptive capacity (e.g., Pia et al., 2012), trust (e.g., Kumar & Zaheer, 2019), and transaction cost (e.g., Wang & Yang, 2019) argue that there should be a negative relationship between network dynamics and firm exploratory innovation. However, most of these research address network dynamics at the inter-firm level, i.e., ego-network, ecosystem, community, and alliance portfolio (e.g., Kumar & Zaheer, 2019; Shi & Zhang, 2019; Shi et al., 2020; Yan & Guan, 2018; Zhang & Luo, 2020; Zhang et al., 2020a). Till now, little is known about intra-firm employee network dynamics and their consequences for firm exploratory innovation.

Intra-firm human capital is crucial for a firm to innovate (Ferreira et al., 2018). Firm innovation relies on R&D employees to make novel knowledge combinations (Grant, 1996; Zhang & Tang, 2020a). Their knowledge combining performance depends on the co-invention network where they are embedded (Paruchuri & Awate, 2017; Wang et al., 2014; Zhang & Tang, 2020a). Much employee co-invention network research has investigated static characteristics, such as density, centrality, structural holes, and centralization. (Tang et al., 2017; Wang et al., 2014; Zhang & Tang, 2017, 2020a). However, few of them address network dynamics. In a dynamic environment, firms and employees need to continuously renew existing knowledge assets (Papa et al., 2021). Network research at the inter-firm level suggests that network dynamics (reconfiguration) of the R&D community or global value chain help achieve such knowledge dynamics (Scuotto et al., 2020; Wang & Yang, 2019). This research shifts attention to the intra-firm perspective and aims to investigate employee co-invention network dynamics. Employee co-invention network dynamics imply two points, namely employee turnover and cross-team movement. Employee turnover means the extent of dynamic change of human capital such as new hires inflow and established staffs outflow. Cross-team movement refers to employees' movement across different teams.

In line with research at the inter-firm level, there might be a possible tension between employee co-inventing network dynamics and firm exploratory innovation. This paper aims to elaborate on both the positive and negative mechanisms. According to the knowledge-based view, stereotyped partnerships might depreciate over time due to the increasing knowledge lock-in effect and the diminishing knowledge combination opportunities (Gulati, 1995). Network dynamics help break knowledge lock-in (Majchrzak et al., 2015) and generate novel knowledge combinations (Yan & Guan, 2018) by fostering knowledge flow. Specifically, employee turnover implies an inflow of external new knowledge (Schubert & Andersson, 2015), and across-team movement facilitates heterogeneous knowledge flow within firm boundaries (Choudhury, 2017). Drawing on the transactive memory system (Moreland et al., 1996), stable and repeat partnerships facilitate a shared awareness of who knows what (Wegner et al., 1991). Network dynamics may hurt it (Liang & Mei, 2019). Specifically, employee turnover threatens cognitive structures (Zhang et al., 2017), and the across-team movement raises the integration costs (Wei & Dang, 2017).

Beyond the mere presence of dual mechanisms, this paper addresses their net effect. Despite being researched a lot, there is no consensus on whether network dynamics exert a net positive or negative impact. Drawing on March's (1991) opinion, exploration highlights a shift towards new knowledge trajectories, which is in line with network dynamics in pursuit of changes, and thus benefits a lot from the bright mechanism (Kumar & Zaheer, 2019; Wang & Yang, 2019). In addition, the damages to the transaction memory system could be slight at the first beginning, yielding a net positive effect. However, as negative network dynamics increase, such a positive effect could decline and even turn negative due to the diminishing marginal returns of knowledge benefits and the rising transaction memory system damages (Zhang et al., 2017). Therefore, this research proposes that the net effect of employee co-inventing network dynamics on firm exploratory innovation may follow an inverted U.

Moreover, this research investigates boundary conditions that may influence the inverted U-shaped effect. Prior research has confirmed that employees and their innovation are structurally embedded in multiple intra-firm networks, including the employee co-invention network and employee-knowledge/knowledge-employee networks (e.g., Zhang & Tang, 2017, 2020a). Although some research has investigated network structures such as density, centralization, and clustering coefficient, few of them explores how these static structures interact with network dynamics and co-impact the firm exploratory innovation. This paper aims to fill the gap by introducing two intra-firm network structures as moderators, namely employee co-invention network centralization and knowledge-employee network equilibrium.

Regarding the employee co-invention network centralization, this paper conceptualizes it to indicate a core-periphery structure where most ties happen within a small number of core employees (Grund, 2012). Evidence suggests that a highly centralized co-invention network would hurt intra-firm coordination among employees by narrowing communication channels, worsening communication saturation, impeding organizational citizenship behaviors, and intensifying knowledge hiding (Arain et al., 2020; Becker et al., 2017; Hong et al., 2020; Yan et al., 2020; Yang et al., 2015). Consequently, it may reduce the knowledge flow benefits and worsen the damages to the transactive memory system, exerting a negative moderation effect.

Regarding the knowledge-employee network equilibrium, this paper conceptualizes it to measure the extent to which knowledge is distributed in equilibrium across employees. This paper argues that a broadly- and evenly- distributed knowledge structure implies more knowledge generalists within a given firm, more knowledge accumulation of employees, and more shared knowledge backgrounds among employees, which facilitate intra-firm knowledge retrieval, cooperation, and absorption process (Anzola-Román et al., 2019; Kuo et al., 2019; Rulke & Galaskiewicz, 2000). As a result, it may enlarge the knowledge flow benefits and strengthen the positive mechanisms, exerting a positive moderation effect.

In sum, this paper aims to extend network dynamics research into the intra-firm perspective and develop a research model that elaborates on the dual mechanism of intra-firm employee co-invention network dynamics on firm exploratory innovation and the boundary conditions. Based on patent data of 76 high-tech firms over 31 years from 1990 to 2020, this paper develops novel quantitative measures for network dynamics and the two-mode network and conducts Negative Binomial fixed-effect panel regressions.

The paper is organized as follows. Section 2 presents the literature review and hypotheses. The data and methods are present in Sect. 3; Next, Sect. 4 reports the regression and robust test results; The last Section concludes with discussions of the main findings, theoretical and managerial implications, some limitations, and directions for future research.

Literature review and hypotheses

Employee co-invention network dynamics and firm exploratory innovation

Despite the dual mechanism, employee co-invention network dynamics may be positively associated with firm exploratory innovation initially due to their couplings in pursuing new knowledge. The rationale for this positive relationship becomes clear when we elaborate on how employee turnover and cross-team movement promote knowledge flow, bring novel knowledge recombination, and prevent knowledge lock-in.

First, employee turnover provides opportunities to acquire external new knowledge. On the one hand, the inflow of new hires entails the new knowledge inflow (Wang et al., 2019). Knowledge affiliated with newcomers tends to be heterogeneous with existing knowledge and close to dynamic environments (March, 1991). On the other hand, the elimination of low performers frees up the resources and reduces conformity pressures (Wei & Dang, 2017). The turnover of star employees reduces commitment to path-dependent knowledge practices, triggers the optimal allocation of knowledge resources, and provides new hires opportunities to develop new perspectives (Tzabbar & Kehoe, 2014), further contributing to exploratory innovation.

Second, employee cross-team movement increases the possibilities of novel knowledge recombination. Novel combinations mainly happed among diverse and remote knowledge elements (Fleming, 2001). As knowledge resides within individual employees (Grant, 1996), mobile employees help transfer remote knowledge and bring diverse expertise to the teams they move. A high rate of employee movement facilitates knowledge search breadth and knowledge transfer efficiency within a firm (Karim & Williams, 2012; Lahiri, 2010), allowing for a much richer possibility of novel knowledge combinations across locations (Singh, 2008). Previous research has reported a positive relationship between employee movement and firm-level innovation (e.g., Choudhury, 2017; Karim & Williams, 2012; Singh, 2008).

Third, both employee recruitment and turnover and cross-team movement help prevent knowledge lock-in. Due to the self-reinforced effect and inertia, teams often depend on the same set of employees and unchanging co-invention partnerships (Shi et al., 2020). However, in fast-paced knowledge-intensive industries, the initial complementarity between co-invention parties' knowledge may diminish over time (Granovetter, 1973). In other words, partnerships formed at a particular point in time might depreciate over time. Network dynamics like employee turnover and movement are adaptive behaviors of an organization in pursuit of new knowledge (Wang & Yang, 2019). Such co-invention dynamics help individual employees break the path dependence and knowledge lock-in (Majchrzak et al., 2015). Also, they help focal firms to expand insights for technology development and increase recognition for innovation opportunities (Zhang et al., 2017).

With the three points given above, employee co-invention network dynamics are positive to firm exploratory innovation. However, as network dynamics increase, absorbing new knowledge and integrating them into novel combinations become difficult, diminishing marginal returns. Meanwhile, exorbitant network dynamics may hurt the transactive memory system (Moreland et al., 1996). For one thing, an excessive rate of employee turnover would threaten cognitive structures, hurt knowledge-sharing practices, and break stable co-invention routines that are useful for coordination (Zhang et al., 2017). For another thing, an exorbitant rate of employee movement across different teams raises the integration costs by conferring new partners in other fields without co-invention history

(Wei & Dang, 2017). Evidence suggests that a well-developed transactive memory system facilitates exploratory innovation (Heavey & Simsek, 2014). Initially, it provides employees an elaborate directory of where knowledge resides (Hammedi et al., 2013), facilitating knowledge recognition and recalls (Zajac et al., 2014), and thus enabling them to search for new knowledge and make novel combinations (Argote & Ren, 2012; Miller et al., 2014). Secondly, it creates psychological safety, trust, and positive social acceptance among team members (Siemsen et al., 2009), leading to more willingness to exchange knowledge with others (Hammedi et al., 2013). Therefore, there may be an optimal level of employee co-invention network dynamics with the most net positive effects.

In sum, this paper proposes that the net effect of employee co-invention network dynamics on firm exploratory innovation may first increase and then declines after a threshold, following an inverted U. The hypothesis is as follows:

H1: Employee co-invention network dynamics have an inverted U-shaped effect on firm exploratory innovation.

Moderating effect of employee co-invention network centralization

As argued above, the bright side of employee co-invention network dynamics mainly derives from the benefits of new knowledge flow and novel knowledge recombination. In contrast, the dark side comes from damages to the transactive memory system. Both sides are contingent on coordination among employees. Well-established coordination may enlarge knowledge flow benefits and mitigate transactive memory system damages. However, employee co-invention network centralization may hurt intra-firm coordination for three reasons.

First, a centralized network structure narrows communication channels (Huang & Cummings, 2011; Yang et al., 2015). Network centralization indicates a core-periphery structure where most co-invention ties happen within a small number of core employees (Grund, 2012). Such a structure may impede communication efficiency and effectiveness (Cummings & Cross, 2003). For peripheral employees, inefficient communication decreases the quantity and quality of information and knowledge access (Sheremata, 2000). For a few core employees, excessive interactions with existing employees may distract their attention, impede their openness, and in turn, decrease their communication with newcomers (Nahapiet & Ghoshal, 1998).

Second, a centralized network structure increases the possibility of coordination saturation. Network centralization reinforces the preferential attachment. In other words, ties are likely to be formed with already popular employees (Yan et al., 2020). It could amplify core employees in the co-invention network and inhibit the contribution of other peripheral members (Becker et al., 2017). Core employees may use their advantageous positions and control the formation of new ties at the cost of coordination among peripheral employees (Hong et al., 2020). The coordination is entirely in the direction of a few core employees, and requirements are concentrated. When coordination requirements surpass the capacity of core employees, the firm suffers from coordination saturation.

Third, a centralized network structure decreases organizational citizenship behaviors (OCB) but exaggerates the social loafing and knowledge hiding effects. In a centralized hierarchy network, most peripheral employees have few opportunities to participate in the firm's innovation, which is likely to decrease their OCB (Yang et al., 2015). Besides, peripheral employees may not have the necessary autonomy, rely on core employees, and not want to bear responsibility (Jansen et al., 2006), leading to excessive bureaucracy and severe social loafing effects (Nickerson & Zenger, 2002). With low OCB, employees are more likely to work independently than cooperate (Organ, 1990). With high social loafing, employees may also suppress their potential absorptive capacity and even exert feigned acceptance (Szulanski, 2000). In addition, knowledge hiding may result in more severe negative consequences in firms with a centralized hierarchy than in firms with a decentralized hierarchy (Arain et al., 2020).

In sum, employee co-invention network centralization impedes communication and coordination among employees. Consequently, knowledge flow benefits accompanied by employee co-invention network dynamics get weakened, while damages to transactive memory system worsen. Given that, employee co-invention network centralization may negatively moderate the inverted U-shaped relationship. The hypothesis is as follows:

H2: Employee co-invention network centralization negatively moderates the inverted U-shaped relationship between employee co-invention network dynamics and firm exploratory innovation.

Moderating effect of knowledge-employee network equilibrium

Firm innovation is embedded not only in the employee co-invention network but also in the knowledge-employee network. Previous network literature has pointed out knowledge benefits acquired through the co-invention network vary depending on knowledge distribution across co-invention partners (Zhang et al., 2017). In line with that, knowledge flow benefits accompanied by network dynamics may depend on the knowledge distribution across mobile employees and their co-invention partners. Knowledge-employee network equilibrium, implying an evenly- and broadly-distributed knowledge structure among employees, may enlarge knowledge flow benefits. The rationale becomes clear when we elaborate on how it promotes knowledge retrieval, cooperation, and absorption.

First, knowledge distribution in equilibrium, implying more generalists within firm boundaries, may enhance intra-firm knowledge retrieval efficiency. As those who have common conceptualization, generalists may help introduce the knowledge and provide retrieval cues with others (Liang et al., 1995). Minimal effort is needed for employees in a given firm to retrieve their required knowledge (Liang, 1994). In contrast, specialists may cause confirmative pressures that may decrease retrieval efficiency and hurt group performance (Rulke & Galaskiewicz, 2000).

Second, knowledge distribution in equilibrium provides a shared knowledge background among employees, facilitating knowledge cooperation. In most instances, knowledge collaboration aims to enlarge cumulated knowledge, learning, or capabilities rather than substitute them (Cantner & Meder, 2007). A tight matchup in terms of the knowledge background promotes cooperation (Anzola-Román et al., 2019). Besides, shared knowledge enables cooperation parties to experience fewer cognitive difficulties, communication costs, and misunderstandings (Lakemond et al., 2016), consequently leading to excellent cooperation performance (Anzola-Román et al., 2019). The larger the shared knowledge base between cooperation parties, the more recombinant innovation can generate through cooperation (Guan & Yan, 2016).

Third, knowledge distribution in equilibrium, implying the knowledge breadth that employees have accumulated and worked on before, is favorable to absorbing new knowledge (Cohen & Levinthal, 1990). Employees need the necessary knowledge accumulation to absorb new knowledge (Grant, 1996). A rich knowledge experience facilitates recognition, access, and integration of new knowledge (Kuo et al., 2019). Besides, a broad knowledge base enables employees to update knowledge by providing them with exposure to different domains (Mannucci & Yong, 2018).

In sum, knowledge-employee network equilibrium enhances knowledge retrieval efficiency, knowledge cooperation effectiveness, and new knowledge absorption capacity within firm boundaries. As a result, it enlarges the knowledge flow benefits. Given that, knowledge-employee network equilibrium may positively moderate the inverted U-shaped relationship. The hypothesis is as follows:

H3: Knowledge-employee network equilibrium positively moderates the inverted U-shaped relationship between employee co-invention network dynamics and firm exploratory innovation.

According to the above relevant literature and hypotheses, the framework in this study is as follows (see Fig. 1):

Method

Research setting, data, and network construction

This research tests hypotheses in four high-tech industries, namely the 3D printing, ICT, wind energy, and lithium battery industries. These industries are knowledge-intensive and fast-paced, where technology upgrading makes existing technologies obsolete rapidly. The accelerated pace of technology updates highlights the exploratory innovation strategy for

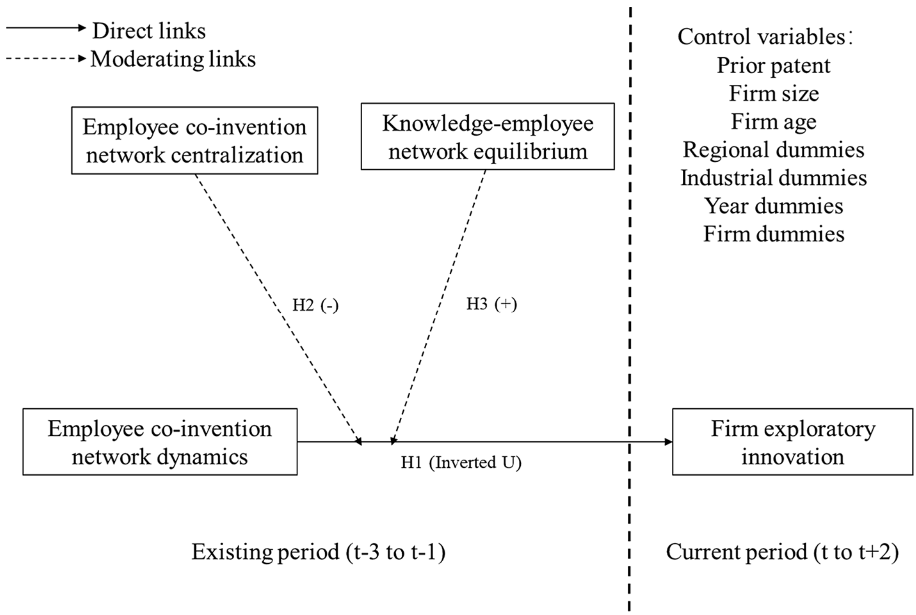

Fig. 1 Research framework

sustainable success. Firms must keep innovative by hiring new employees with advanced novel knowledge and reconfigure the composition of R&D teams. In this sense, these industries provide observations for exploratory innovation and employee co-invention network dynamics. In addition, these industries have a propensity for patenting and thus offer rich patent data.

I extract patent data from the frequently-adopted Derwent Innovation Index database (DII). I chose this database because it is the most comprehensive patent database worldwide, covering patents issued by more than 100 countries and 40 patent authorities, including USPTO, EPO, JPO and SIPO, and so on. Therefore, patents extracted from DII can reflect the developmental state of global technology. To accurately identify and capture patents in 3D printing, ICT, wind energy, and lithium battery industries from the DII database, I closely followed the IPC-based searching strategies (see Appendix Table 6) utilized by OECD (2008). To select sample firms, I carefully check the patentees of each patent. After a thorough cleaning up and counting, I finally identified 76 top firms with numerous inventive patents and long patenting experience. Specifically, there are 20 firms are from 3D printing technology, ICT, and lithium battery, respectively, and 16 firms from wind energy (see Appendix Table 7).

I download patent information, including application year, inventor, international patent classification (IPC) code, and patent family. A patent often involves two or more inventors and IPC codes. Using the joint invention information among employees, I construct the employee co-invention networks. Considering the availability of data, I take IPC codes as proxies of knowledge elements. Following the common practice, four-digit IPC codes are exploited in this paper to denote the knowledge elements (Yan & Guan, 2018; Zhang & Tang, 2020a). Using the co-occurrence information between inventors and four-digit IPC codes, I construct the knowledge-employee networks. Networks are constructed every 3-year moving window (see also Zhang & Tang, 2017, 2020a) with the help of Science of Science (Sci2) and Organizational Risk Analyzer (ORA) software.

I construct networks for each sample firm according to its patent experience. For a firm that starts patenting in 1990 and ends in 2020, I take its patents in the first 5 years (1990–1994) as IPC code portfolios to identify exploratory patents in a subsequent year (1995). I count firm exploratory patents in the last 3-year period (2018–2020) as outcomes of network dynamics in the preceding 3-year period (2015–2017). I construct employee co-invention networks and two-mode networks using patents in 1990–2017. What needs to be noted is that I take the first employee co-invention network (1990–1992) as the reference substance to calculate network dynamics in the subsequent period (1993–1995). Therefore, the first observation of network dynamics for firms that starts patenting in 1990 and ends in 2020 is in 1993–1995, and the last one is in 2015–2017. In turn, I get 1077 firm-year observations.

Measurements

Dependent variable

Firm exploratory innovation (FEI). I adopt patent-based indicators to measure innovation performance (Zhang & Tang, 2020a, 2020b; Zhang et al., 2020a). I follow the method developed by Gilsing et al. (2008) to distinguish the exploratory patents from exploitative ones. Supposing one (or more) four-digital IPC code of a patent in the observation year is absent in the focal firm's preceding 5-year IPC portfolio, I count it as an exploratory patent, otherwise an exploitative patent. As it takes time to innovate and patent, I measure firm exploratory innovation by counting exploratory patents of subsequent 3 years. To overcome the limitation of the simple count, I weight each patent by its number of patent authorities (see also Zhang & Tang, 2020a, 2020b). The formulas are as follows:

$$\mathrm{FEI} = \sum_{j=1}^{n} Wj$$

where n denotes a firm's number of exploratory patents in the observed 3-year period, and W_j represents the number of authorities of patent j. I calculate this variable by writing a program with Matlab.

Independent variables

Employee co-invention network dynamics (ECND). Network dynamics refer to ties changes in previous literature (Ahuja et al., 2012). For example, Yan and Guan (2018) measure scientists' co-invention network dynamics by counting co-invention tie changes between two periods. Given that, I calculate employee co-invention network dynamics by comparing the co-invention network of the current period with the one of the preceding period. Considering that a tie may dissolve naturally after 3 years (Paruchuri, 2010) and an activated tie with repeat partners after 3 years' separation may involve new knowledge (Cannella & McFadyen, 2016), I adopt a 3-year moving window for network comparison. To exclude the impact of scale, I sum the newly-added ties and the lost ties of the current period and then divided them by the total number of network ties of the preceding period. The formula is as follows:

$$\mathrm{ECND} = \frac{N_{Ti} + N_{Td}}{N_{T-1}}$$

N_{Ti} indicates the number of newly-added co-invention ties of the current period; N_{Td} indicates the number of lost co-invention ties of the current period; N_{T-1} is the total number of co-invention ties of the preceding period. If there are no tie changes between two periods, the variable takes the minimum value, zero.

Moderation variables

Employee co-invention network centralization (ECNC). Following previous practice (Luo, 2010), I calculate the degree centralization of the co-invention network as follows:

$$\mathrm{ECNC} = \frac{\sum_{i=1}^{n} \left[C_D(n*) - C_D(n_i)\right]}{\max \sum_{i=1}^{n} \left[C_D(n*) - C_D(n_i)\right]}$$

$C_D(n_i)$ indicates the degree centrality of node i, and $C_D(n^*)$ indicates the maximum value of all $C_D(n_i)$; n indicates the number of nodes. The numerator represents the sum of the difference between the maximum centrality of the network and other nodes' centrality. The denominator is the maximum possible value for the numerator.

Knowledge-employee network equilibrium (KENE). The knowledge-employee network, defined as two disjoint sets of nodes (knowledge element and employee) and ties between them, can precisely record knowledge distribution across employees. Specifically, The knowledge-employee network equilibrium to measures how knowledge is distributed broadly and evenly. Referring to the Entropy index proposed by Shannon (1948), I develop the measure as follows:

$$\mathrm{KENE} = -\sum_{i=1}^{s} P_i(\ln P_i)$$

P_i indicates the proportion of knowledge-employee ties that the employee i holds of all knowledge-employee ties; s means the number of employees of a given firm. If a single employee has all the ties, the variable takes the minimum value, zero. It rises when a large number of employees hold an equal proportion of the ties.

Control variables

Previous patent. This research employs previous patent as the control variable to control for unobserved heterogeneity in sample firms' patenting activities (Zhang & Tang, 2020a). Previous patent is the number of patents acquired by a firm in the 5 years before it entered the sample.

Firm age. Firm age is associated with organizational learning and path dependence (Cohen & Levinthal, 1990), both related to exploration. Thus it needs to be controlled.

Firm size. A firm's size is associated with its innovation strategy, capability, and outcomes (Zhang & Tang, 2020a, 2020b). Thus it needs to be controlled. I adopt the log-transformed number of inventors in the observation period as its proxy.

Geographical dummies. Patenting propensities and innovation patterns vary across regions (Zhang & Tang, 2018, 2020b). I employ geographical dummies to control the variation. As most sample firms come from Japan, America, Mainland China, Korea, and Europe, I employ five geographical dummies and control them. For instance, if a firm comes from Europe, the corresponding dummy Europe takes the value 1, otherwise 0. The default indicates countries other than these five countries mentioned above.

Industrial dummies. Patenting propensities and innovation patterns vary across industries (Zhang & Tang, 2017, 2020a). I employ industrial dummies to control the variation. As sample firms come from four industries, I adopt three dummies. If a firm belongs to the 3D printing, ICT, or wind energy industry, the corresponding industrial dummy takes the value of 1, otherwise 0. The default is the lithium battery industry.

Statistical methods

The dependent variable, firm exploratory innovation, takes the form of a nonnegative integer count. Applying a linear regression model to such data will yield inconsistent, inefficient, and biased coefficient estimates. Thus, Poisson or Negative Binomial regression should be adopted to handle these problems. Poisson regression strictly supposes that the dependent variable's mean and standard deviation should be equal ($\mathrm{Var}(yi) = E(yi) = \lambda i$). However, firm exploratory innovation in this study exhibits over-dispersion, which will underestimate the standard errors of the Poisson regression. Therefore, I adopt the Negative binomial regression model that permits the over-dispersion.

$$p(Y_i = y_i) = \frac{\Gamma(y_i + \frac{1}{\alpha})}{\Gamma(\frac{1}{\alpha})\Gamma(1 + y_i)} \left(\frac{1}{1 + \alpha\lambda_i}\right)^{\frac{1}{\alpha}} \left(\frac{\alpha\lambda_i}{1 + \alpha\lambda_i}\right)^{y_i}$$

$$E(y_i) = \lambda_i, \quad \mathrm{Var}(Y_i) = \lambda_i + \alpha\lambda_i^2, \quad \text{for } \alpha > 0$$

According to Hausman tests at firm and time dimensions, I adopt the two-way fixed-effects panel regression. To mitigate the endogeneity and simultaneity, I employ a longitudinal design. To confirm the robustness, I conduct several tests. First, I process the weighted exploratory patent count with logarithm and run the linear fixed-effect panel regression. Second, I drop the observation years that suffer from serious value missing and run regression on a shorter panel from 2005 to 2017. At last, I calculate firm exploitative innovation and regress on it.

Results

Regression results

Table 1 displays variable description and correlations. As displayed, correlations among main variables are all at a moderate and reasonable level. Specifically, employee co-invention network dynamics (ECND) has a positive correlation with firm exploratory innovation (FEI) ($r=0.099$, $p<0.01$). Employee co-invention network centralization (ECNC) has a negative correlation with FEI ($r=-0.061$, $p<0.05$). Knowledge-employee network equilibrium (KCNE) has a positive correlation with FEI ($r=0.195$, $p<0.05$).

Table 1 Mean, SD, correlations of main variables

	1	2	3	4	5	6	7
1 FEI							
2 ECND	0.099**						
3 ECNC	−0.061*	0.230**					
4 KENE	0.195**	−0.163**	−0.434**				
5 Previous patent	0.023	−0.139**	−0.466**	0.402**			
6 Firm age	−0.023	−0.072*	−0.073*	0.179**	−0.042		
7 Firm size	−0.008	−0.140**	−0.467**	0.386**	0.866**	−0.048	
N	1077	1077	1077	1077	1077	1077	1077
Mean	40.764	0.884	0.059	2.717	62.895	95.578	210.152
S.D	44.124	1.005	0.053	0.486	71.015	40.506	222.303
Min	0	−0.032	0	0.639	2	6	4
Max	293	14.321	0.455	4.164	550	227	1497

*$p<0.05$, **$p<0.01$

FEI means firm exploratory innovation; ECND means employee co-invention network dynamics; ECNC means employee co-invention network centralization; KENE means knowledge-employee network equilibrium

Table 2 Negative Binomial two-way fixed panel regressions

Variable	Firm exploratory innovation						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ECND		0.024*	0.136***	0.136***	0.256***	0.140***	−0.187
		(0.012)	(0.027)	(0.027)	(0.051)	(0.028)	(0.136)
ECND_Square			−0.011***	−0.011***	−0.024**	−0.012***	0.017
			(0.003)	(0.003)	(0.008)	(0.003)	(0.014)
ECNC				0.086	1.034*		
				(0.369)	(0.525)		
ECND × ECNC					−1.200**		
					(0.428)		
ECND_Square × ECNC					0.098**		
					(0.033)		
KENE						0.071	−0.045
						(0.052)	(0.070)
ECND × KENE							0.130*
							(0.053)
ECND_Square × KENE							−0.011*
							(0.006)
Previous patent	−0.002*	−0.002*	−0.002*	−0.002*	−0.001*	−0.002*	−0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm age	0.003 +	0.003*	0.003 +	0.003 +	0.002	0.003 +	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm size	−0.000	−0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Geographical dummies	Included	Included	Included	Included	Included	Included	Included
Industrial dummies	Included	Included	Included	Included	Included	Included	Included

Table 2 (continued)

Variable	Firm exploratory innovation						
Firm dummies	Included	Included	Included	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included	Included	Included	Included
_cons	1.971***	1.940***	1.879***	1.872***	1.838***	1.693***	1.974***
	(0.160)	(0.161)	(0.162)	(0.164)	(0.166)	(0.213)	(0.237)
N	1075	1075	1075	1075	1,075	1075	1075
Log likelihood	−3903.2	−3901.2	−3891.2	−3891.2	−3885.9	−3890.3	−3887.2
Wald chi2 test	518.49***	526.60***	563.71***	563.76***	578.74***	566.76***	578.09***

Table 2 presents the results of Negative Binomial two-way fixed panel regression. In model 1, control variables (previous patent, firm age, firm size, geographical dummies, industrial dummies, firm dummies, and year dummies) are entered. Models 2 and 3 are run to test the quadratic impact of ECND on FEI. As presented, ECND has a positive impact and its squared item has a negative impact (see model 3, $\beta_1 = 0.136$, $p_1 < 0.001$; $\beta_2 = -0.011$, $p_2 < 0.001$, respectively), which suggests an inverted U shape. Thus hypothesis 1 is supported. Models 4 and 5 are run to test the moderation impact of ECNC. As presented, ECNC × ECND has a negative impact, and ECNC × ECND_Square has a positive impact (see model 5, $\beta_1 = -1.200$, $p_1 < 0.01$; $\beta_2 = 0.098$, $p_2 < 0.01$, respectively). Following the procedure developed by Dawson (2014), I plot the quadratic two-way interaction effect in Fig. 2. As shown, when ECNC increases, the inverted U-shaped curve moves downward and to the left. Thus hypothesis 2 is supported. Models 6 and 7 are run to test the moderation impact. As presented, KENE × ECND has a negative impact, and KENE × ECND_Square has a positive impact on FEI (see model 7, $\beta_1 = 0.130$, $p_1 < 0.05$; $\beta_2 = -0.011$, $p_2 < 0.05$, respectively). Following the same way, I plot the results in Fig. 3. As shown, when KENE increases, the inverted U-shaped curve moves upward and to the right. Thus hypothesis 3 is supported.

Robust test results

To verify the robustness, I conduct several alternative regressions. The first one is linear fixed-effect panel regression on the logarithmic exploration innovation. As displayed in Table 3, the inverted U-shaped effect of ECND (see model 2, $\beta_1 = 0.160$, $p_1 < 0.001$; $\beta_2 = -0.013$, $p_2 < 0.001$), the negative moderation effect of ECNC (see model 3, $\beta_1 = -1.422$, $p_1 < 0.01$; $\beta_2 = 0.108$, $p_2 < 0.01$), and the positive moderation effect of KENE (see model 4, $\beta_1 = 0.197$, $p_1 < 0.01$; $\beta_2 = -0.016$, $p_2 < 0.01$) are confirmed.

Second, I conduct Negative Binomial fixed-effect regression on the truncation panel from 2005 to 2017. As displayed in Table 4, the inverse U-shaped effect of ECND (see model 2, $\beta_1 = 0.142$, $p_1 < 0.001$; $\beta_2 = -0.011$, $p_2 < 0.01$), the negative moderation effect of ECNC (see model 3, $\beta_1 = -1.390$, $p_1 < 0.05$; $\beta_2 = 0.295$, $p_2 < 0.001$), and the positive moderation effect of KENE (see model 4, $\beta_1 = 0.316$, $p_1 < 0.001$; $\beta_2 = -0.049$, $p_2 < 0.05$) are confirmed.

Third, I run Negative Binomial fixed-effect panel regression on firm exploitative innovation. As displayed Table 5, ECND has neither significant positive nor negative impacts on firm exploitative innovation (see model 1, $\beta = -0.012$, $p_1 = 0.338$). The inverse U-shaped effect isn't confirmed (see model 2, $\beta_1 = -0.003$, $p_1 = 0.180$; $\beta_2 = -0.001$, $p_2 = 0.132$). Neither the negative moderation effect of ECNC (see model 3, $\beta_1 = -0.684$, $p_1 = 0.91$; $\beta_2 = 0.058$, $p_2 < 0.05$) nor the positive moderation effect of KENE are supported (see model

Table 3 Logarithmic firm exploratory innovation

Variable	Model 1	Model 2	Model 3	Model 4
ECND		0.160***	0.291***	−0.327*
		(0.034)	(0.054)	(0.156)
ECND_Square		−0.013***	−0.025***	0.026
		(0.003)	(0.005)	(0.015)
ECNC			1.577**	
			(0.605)	
ECND × ECNC			−1.422**	
			(0.482)	
ECND_Square × ECNC			0.108**	
			(0.034)	
KENE				−0.216**
				(0.083)
ECND × KENE				0.197**
				(0.062)
ECND_Square × KENE				−0.016**
				(0.006)
Previous patent	−0.001 +	−0.001 +	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Firm age	0.005	0.007	0.007	0.008
	(0.006)	(0.006)	(0.006)	(0.006)
Firm size	−0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Geographical dummies	Included	Included	Included	Included
Industrial dummies	Included	Included	Included	Included
Firm dummies	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included
_cons	3.306***	2.961***	2.785***	3.420***
	(0.648)	(0.645)	(0.652)	(0.662)
N	1077	1077	1077	1077
R-squared	0.3739	0.3877	0.3951	0.3944
F	25.55	24.87	22.84	22.77

*+ $p < 0.08$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

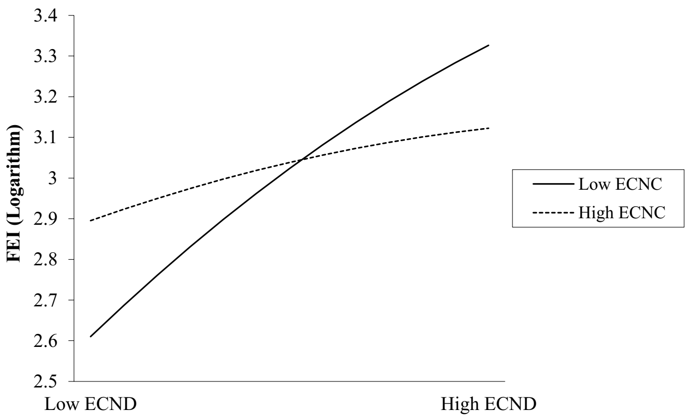

Fig. 2 The moderating effect of ECNC

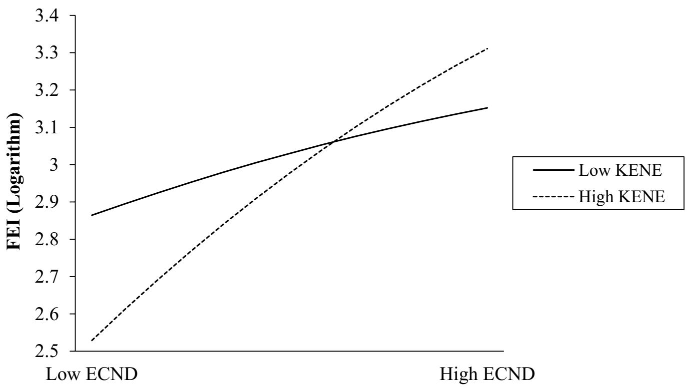

Fig. 3 The moderating effect of KENE

4, $\beta_1=0.070$, $p_1=0.128$; $\beta_2=-0.006$, $p_2=0.220$). The results suggest that firm exploitation innovation has different requirements on network dynamics, co-invention patterns, or knowledge distribution with firm exploratory innovation.

Conclusions and discussion

Main findings

Inter-firm network partnerships, such as R&D collaborations (Zhang & Luo, 2020), alliances (Petruzzelli, 2019), and M&As (Zhang et al., 2020b), are widely taken as the micro-foundations of strategic ambidexterity. Drawing on the dynamic perspective, scholars have confirmed the correlation between inter-firm network dynamics (or stability, inertial) partnerships and firm exploratory innovation (e.g., Kumar & Zaheer, 2019; Yan & Guan, 2018; Zhang & Luo, 2020). However, little is known about intra-firm network dynamics and

Table 4 Negative Binomial fixed-effect panel regression (2005–2017)

Variable	Firm exploratory innovation			
	Model 1	Model 2	Model 3	Model 4
ECND		0.142***	0.522***	−0.597**
		(0.034)	(0.098)	(0.199)
ECND_Square		−0.011**	−0.118***	0.094*
		(0.003)	(0.029)	(0.038)
ECNC			1.361*	
			(0.649)	
ECND × ECNC			−1.390*	
			(0.557)	
ECND_Square × ECNC			0.295***	
			(0.077)	
KENE				−0.194*
				(0.084)
ECND × KENE				0.316***
				(0.086)
ECND_Square × KENE				−0.049*
				(0.019)
Previous patent	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Firm age	0.004**	0.004*	0.003*	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Firm size	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Geographical dummies	Included	Included	Included	Included
Industrial dummies	Included	Included	Included	Included
Firm dummies	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included
_cons	1.998***	1.942***	1.772***	2.311***
	(0.182)	(0.183)	(0.193)	(0.265)
N	807	807	807	807
Log likelihood	−2771.9	−2763.3	−2749.8	−2755.1
Wald chi2 test	473.94***	509.06***	553.49***	541.94***

*+ $p < 0.08$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

their consequences for firm exploratory innovation. To address the research gap, this paper develops a research model that explains the dual mechanism of intra-firm employee co-invention network dynamics on firm exploratory innovation and its boundary conditions. The main findings are as follows:

First, employee co-invention network dynamics have a positive curvilinear effect on firm exploratory innovation. The result is consistent with Wang and Yang's (2019) research on the community network that reports an inverted U-shaped relationship between network dynamics and firm exploratory innovation. Despite the dual mechanism, evidence from the inter-firm network research suggests that the positive mechanism dominates the exploratory innovation, leading to a net positive effect (e.g., Kumar & Zaheer, 2019; Pia et al., 2012; Schubert & Andersson, 2015; Yan & Guan, 2018). In addition, the robust test reports a negative but not significant correlation between employee co-invention network dynamics and firm exploitative innovation. The result confirms Yan and Guan's (2018) conclusion that network dynamics have a more powerful positive impact on exploratory innovation than exploitative innovation.

Second, employee co-invention network centralization plays a negative moderation role. Previous research examining the relationship between network centralization and innovation performance has suggested conflicting views and mixed results. On the one hand, network centralization means collective learning processes and promotes collective wisdom (e.g., Wisdom et al., 2013). On the other hand, it narrows communication channels, worsens communication saturation, and decreases OCB among employees (e.g., Yan et al., 2020; Yang et al., 2015). Centralization versus decentralization presents as a tradeoff in many topics, such as decision making (e.g., Arcuri and Dari-Mattiacci, 2010) and voice (e.g., Sherf et al., 2018). Regarding the specific case of network dynamics and exploratory innovation, this research highlights coordination among employees and addresses network centralization from the dark side. The result aligns with Jansen et al.'s (2006) and Huang and Cummings's (2011) research that suggests a centralized structure favors exploitative innovation but hurts exploratory innovation.

Third, knowledge-employee network equilibrium plays a positive moderation role. Zhang and Tang (2020a, 2020b) have concluded three kinds of intra-firm networks: employee co-invention network, knowledge occurrence network, and two-mode knowledge-employee/employee-knowledge network. While much research has investigated the first two networks, few explore how the two-mode network except for several pioneer research (e.g., Zhang & Tang, 2017, 2020a, 2020b). This research focuses on knowledge-employee network equilibrium that indicates the extent to which knowledge is distributed broadly and evenly across employees. The result suggests that it can enlarge knowledge flow benefits accompanied by network dynamics. Due to the novelty of the concept, there is a lack of related research. Nevertheless, evidence from knowledge management research may support the above conclusion by highlighting the individual employees' knowledge accumulation in pursuit of exploratory learning (e.g., Decaro et al., 2015), absorptive capacity (e.g., Bogers et al., 2018), and creative productivity (e.g., Kuo et al., 2019). The conclusion also confirms Santoro et al.'s (2021) opinion that firm knowledge management may positively interact with dynamic capability and co-impact firm ambidexterity.

Theoretical contributions and practical implications

This research makes several theoretical contributions. First, it provides new insights into the dual mechanisms of network dynamics by extending the intra-firm perspective. Prior research mainly investigates network dynamics at the inter-firm level and addressed the positive mechanism drawing on external knowledge acquisition (e.g., Kumar & Zaheer, 2019), social capital (e.g., Yan & Guan, 2018), and network inertial (e.g., Wang & Yang, 2019) as well as the negative mechanism drawing on absorptive capacity (e.g., Pia et al., 2012), trust (e.g., Kumar & Zaheer, 2019), and transaction cost (e.g., Wang & Yang, 2019). This research goes beyond this dominant focus and highlights the intra-firm perspective. Specifically, this research focuses on the employee co-inventing network and considers two specific types of dynamics: employee turnover and across-team movement. Based on the knowledge-based view and transactive memory system, this research proposes positive and negative mechanisms. Beyond the mere presence of the dual mechanism, this research discusses their net effect and conceptualizes it as an inverted U shape. Furthermore, this research draws on the network embeddedness perspective and confirms the moderation effects of employee co-invention network and knowledge-employee network. In sum, this research deepens our understandings of employee co-invention network dynamics by elaborating the connotation, dual mechanisms, and boundary conditions.

Second, it contributes to innovation ambidexterity literature by confirming that two types of innovation require different network dynamics and structures. The difference between exploration and exploitation can be analyzed by referring to the different knowledge trajectories they entail. Exploitation builds on existing consolidated knowledge bases, while exploration highlights a shift towards new knowledge trajectories (March, 1991). Therefore, exploration innovation that pursues new knowledge may have more positive couplings with network dynamics (see also Kumar & Zaheer, 2019; Wang & Yang, 2019). By contrast, exploitative innovation that emphasizes consolidated knowledge may disaccord with network dynamics. Considering that exploration requires intensive interactions, employee co-invention network centralization that hurts communication and coordination among employees may play a more powerful negative role in the relationship between network dynamics and exploratory innovation. Similarly, considering that exploration needs extensive search for remote and diverse knowledge, knowledge-employee network equilibrium that facilitates the knowledge retrieval efficiency, knowledge cooperation effectiveness, and new knowledge absorption capacity may play a more powerful positive role in the relationship between network dynamics and exploratory innovation. In sum, this research enriches the antecedent research of innovation ambidexterity by revealing the differential roles of network dynamics, centralized hierarchy, and knowledge distribution equilibrium.

Third, it advances social network analytical methods by developing novel measures for intra-firm network dynamics and the two-mode network. There are two limitations of extant social network analysis. For one thing, while static network structures like centrality, structural holes, and centralization have been investigated a lot (e.g., Tang et al., 2017; Zhang & Tang, 2017, 2018), network dynamics research is still at an early stage. Referring to some pioneering research (e.g., Kumar & Zaheer, 2019; Wang & Yang, 2019; Yan & Guan, 2018), this research develops a quantitative measure for intra-firm employee co-invention network dynamics. For another thing, most research focuses on the one-mode network (i.e., co-inventing network, alliance network, and knowledge occurrence network) and neglects the two-mode network (Shi et al., 2019; Tang et al., 2017; Zhang & Tang, 2020b). Two-mode networks consist of two sets of nodes (i.e., employees and knowledge elements) and ties across them (Zhang & Tang, 2017, 2020a). The knowledge-employee network, as a two-mode network, can precisely record knowledge distribution. This research develops a measure based on the Entropy index to measure the equilibrium of knowledge distribution. In sum, this research enriches the network research tools and extends the network research scope by developing measures for intra-firm network dynamics and two-mode network equilibrium.

This research also provides some managerial implications. First, based on the findings that exploratory innovation and exploitative innovation have different requirements on network dynamics and structures, firm managers need to be aware of the tensions arising from the ambidextrous innovation strategy. In most cases, a firm cannot achieve both at the same time. Managers in fast-paced and knowledge-intensive industries should implement more knowledge exploration activities and attach importance to the factors that have positive impacts (i.e., co-invention network dynamics). Coupling firms' strategic options with network dynamics provide a complete way of explaining how firms can improve their innovative capacity (Belso-Martinez & Diez-Vial, 2018). Second, firm managers can configure

Table 5 Negative Binomial fixed-effect panel regression on exploitative innovation

Variable	Firm exploitative innovation			
	Model 1	Model 2	Model 3	Model 4
ECND	−0.012	−0.003	0.053	−0.163
	(0.012)	(0.024)	(0.040)	(0.119)
ECND_Square		−0.001	−0.006	0.013
		(0.002)	(0.004)	(0.012)
ECNC			−1.249**	
			(0.457)	
ECND × ECNC			−0.684	
			(0.405)	
ECND_Square × ECNC			0.058*	
			(0.028)	
KENE				0.239***
				(0.058)
ECND × KENE				0.070
				(0.046)
ECND_Square × KENE				−0.006
				(0.005)
Previous patent	0.001*	0.001*	0.001*	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Firm age	−0.002*	−0.002*	−0.002*	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Firm size	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Geographical dummies	Included	Included	Included	Included
Industrial dummies	Included	Included	Included	Included
Firm dummies	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included
_cons	2.240***	2.233***	2.367***	1.712***
	(0.143)	(0.144)	(0.145)	(0.202)
N	1,075	1,075	1,075	1,075
Log likelihood	−6045.4	−6045.3	−6029.2	−6021.4
Wald chi2 test	235.66***	235.84***	268.64***	291.55***

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

intra-firm co-invention network dynamics in two ways: Managers should allocate new hires to existing teams rationally. Meanwhile, it is necessary to cultivate an open and cooperative culture to encourage co-invention between new hires and established employees. Managers need to break team boundaries and reconfigure team composition regularly. However, it does not mean that firms should pursue dynamism blindly at the cost of the transactive memory system. When employee turnover and cross-team movements exceed the threshold, managers need to curb them. Third, focusing on co-invention network dynamics is not enough for exploratory innovation. For firms from emerging countries where centralized architecture is more legitimate and prevails more often (Yang et al., 2015), managers need more incentive or discretion to decentralized the co-invention network. Managers should build up learning platforms, speed up critical generalized knowledge diffusion, and cultivate more generalists.

Limitations and future researches

There are some limitations. First, regarding the measure, patents could not represent firm innovation comprehensively due to the secrecy, patent thicket, and non-patenting propensity. Future research may include innovation outcomes, such as new product development, trademark registration, App development, software copyright registration, etc. Second, this research only involves sample firms from knowledge-intensive and fast-paced industries. Future research can duplicate the research design and generalized it to other traditional contexts. Third, coordination hierarchy and knowledge distribution may interact with each other. Future research may investigate their co-moderating mechanisms.

Appendix 1

See Tables 6 and 7.

Table 6 Definitions of search queries for patents in four fields

Searching sets	Searching terms
ICT	IP = (H01J-011/00 or H01J-013/00 or H01J-015/00 or H01J-017/00 or H01J-019/00 or H01J-021/00 or H01J-023/00 or H01J-025/00 or H01J-027/00 or H01J-029/00 or H01J-031/00 or H01J-033/00 or H01J-040/00 or H01J-041/00 or H01J-043/00 or H01J-045/00 or G01S or G08C or G09C or H01P or H01Q or H1S5 or H03B or H03C or H03D or H03H or H03M or H04B or H04J or H04K or H04L or H04M or H04Q or G11B or H03F or H03G or H03J or H04H or H04N or H04R or H04S or H04N-001 or H04N-011 or H04N-003 or H04N-005 or H04N-009 or H04N-013 or H04N-015 or B07C or B41J or B41K or G02F or G03G or G05F or G09F or G09G or G10L or G11C or H03K or H03L or G06C or G06D or G06E or G06F or G06G or G06J or G06K or G06M or G06N or G06Q or G06T or G07B or G07C or G07D or G07F or G07G or G01B or G01C or G01D or G01F or G01G or G01H or G01J or G01K or G01L or G01M or G01N or G01P or G01R or G01V or G01W or G05B or G08G or G09B or H01B-011/00 or H01L or G02B-006/00 or H05B or H05C or H05F or H05K) and PN = (CN1*)
3D printing	IP = (H04N-013/00 or H04N-015/00 or G02B-027/22 or G02B-027/00 or G02C-005/00 or G02F-001/00 or G03C or G03B-019/00 or G03B-035/00 or G06T-009/00 or G06T-015/00 or G06T-017/00 or G06T-019/00 or H04N-005/00 or H04N-007/00 or H03M-013/00) and PN = (CN1*)
Wind energy	IP = (F03D* or B60L-008/00 or B63H-013/00) and PN = (CN1*)
lithium battery	IP = (H01M-004/00 or H01M-010/00 or H01M-002/00 or H02J-007/00 or H01M-006/00 or H02H-007/00 or C01B-025/00 or C01B-031/00 or C01D-015/00 or C01G-045/00 or C01G-051/00 or C01G-001/00 or C01G-053/00 or G01R-031/00) and PN = (CN1*)

Table 7 Information of 76 sample firms

Industry	Firm	Country	Industry	Firm	Country
3D printing	SONY	Japan	Lithium Battery	ABB	Switzerland
	SAMSUNG	Korea		BYD	China
	PHILIPS	Netherlands		LG	Korea
	PANASONIC	Japan		SONY	Japan
	LG	Korea		HONDA	Japan
	THOMSON	Canada		BOSCH	Germany
	QUALCOMM	America		TOSHIBA	Japan
	TOSHIBA	Japan		TOYOTA	Japan
	MICROSOFT	America		FOXCONN	Taiwan
	CANON	Japan		ELECTRIC POWER GROUP	China
	NEC	Japan		UNIV QINGHUA	China
	SHARP	Japan		NEC	Japan
	SIEMENS	Germany		NISSAN	Japan
	MITSUBISHI	Japan		SAMSUNG	Korea
	TCL	China		SANYO	Japan
	NOKIA	Finland		PANASONIC	Japan
	EPSON	Japan		GE ENERGY POWER	America
	INTEL	America		GENERAL MOTORS	America
	HUAWEI	China		SIEMENS	Germany
	FUJIFILM	Japan		SUMITOMO	Japan
ICT	ADC	America	Wind Energy	ZF	Germany
	ALCATEL	France		VESTAS	Denmark
	CORNING	America		UNIV XIAN JIAOTONG	China
	FUJIKURA	Japan		ELECTRIC POWER GROUP	China
	FURUKAWA	Japan		UNIV SHANGHAI JIAOTONG	China
	LG	Korea		SUMITOMO	Japan
	FUJITSU	Japan		SIEMENS	Germany
	HITACHI	Japan		NTN	Japan
	DRAKA	America		MITSUBISHI HEAVY	Japan
	FOXCONN	Taiwan		FOXCONN	Taiwan
	PANASONIC	Japan		FUJITSU	Japan
	3 M	America		GE ENERGY POWER	America
	OMRON	Japan		GUODIAN	China
	PHILIPS	Netherlands		BOSCH	Germany
	SHARP	Japan		ALSTOM	France
	SIEMENS	Germany		ABB	Switzerland
	SAMSUNG	Korea			
	SONY	Japan			
	SUMITOMO	Japan			
	TOSHIBA	Japan			

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