MS. Dissertation in Engineering

Inter-organizational Collaboration and Optimal Cognitive Proximity : Moderating Effect of Knowledge Complexity

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Inter-organizational Collaboration and Optimal Cognitive Proximity : Moderating Effect of Knowledge Complexity

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Abstract

Inter-organizational Collaboration and Optimal Cognitive Proximity : Moderating Effect of Knowledge Complexity

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This study examines the two-sided effects of cognitive proximity in the context of collaborative innovation, focusing on the moderating effect of knowledge complexity. Utilizing USPTO patent data of US biotechnology sector, this research confirmed an inverse U-shaped effect of cognitive proximity on collaborative innovation. The optimal level of cognitive proximity increases with higher level of knowledge complexity, which shows positive moderating effect of complexity on the proximity effect on collaborative innovation. The marginal effect of cognitive proximity also increases in complex fields, indicating that proximity plays stronger role as knowledge complexity increases.

This indicates that while cognitive proximity enhances knowledge absorption, the presence of knowledge complexity introduces friction, hindering knowledge diffusion and learning. Organizations that share more complex knowledge can achieve optimal collaborative performance by partnering with cognitively close counterparts. However, collaboration performance is lower than optimal point of lower complex fields, even if organization achieve optimal cognitive distance. These insights offer valuable implications for collaboration strategies for organizations and provide guidance for policymakers and stakeholders in fostering innovation networks and creating supportive ecosystems.

Keywords: Inter-organizational Collaboration, Proximity, Knowledge complexity
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Contents

List of Tables

List of Figures

Chapter 1. Introduction

Knowledge generation is a process of combining existing knowledge to create novelty, and diversity is important in creating ‘novel’ innovation (Fleming, 2001; Nonaka & Takeuchi, 1995; Schumpeter, 1934, 1939). In today's rapidly evolving society, knowledge is growing at an unprecedented rate in terms of both quantity and speed. This abundance of knowledge leads to increased specialization and division of labor, driving actors to seek collaboration (Fleming & Sorenson, 2004; Graf & Kalthaus, 2018). However, the rapid pace of knowledge expansion poses a challenge for individuals to ensure the necessary diversity for novel combinations (Cantner & Rake, 2014). Firms have to engage with different types of partners to acquire ideas and resources from the external environment to stay innovative and abreast of competition (Dahlander & Gann, 2010). In this era, therefore, knowledge generation is a cumulative and interactive process of knowledge exchange and diffusion among different actors. (Ahuja, 2000; Powell, 1998; Powell et al., 1996). The ability to create and learn from knowledge is now a critical driver of competitive advantage for both firms and regions. Therefore, it is crucial to comprehend the dynamics of collaborative knowledge creation among actors (Boschma, 2005).

Many proximity literatures have been delved into the impact of proximity on learning, knowledge creation and innovation (R. Boschma, 2005). The underlying premise of proximity research is that the similarity and difference between actors' characteristics influence their interactions within collaborative spaces (Caragliu, 2022). Specifically, in terms of knowledge diffusion and inter-organizational learning, proximity plays a role in either accelerating or impeding the flow of knowledge, ultimately affecting the speed of knowledge exchange. Notably, (R. Boschma, 2005) introduces a five-dimensional proximity framework that encompasses geographical, organizational, institutional, social, and cognitive spaces. In the fields of economics of innovation and innovation management, cognitive proximity gets particular highlights, align with the concept of knowledge base (Balland et al., 2020; Davids & Frenken, 2018).

Many empirical evidences investigated the linear impacts of cognitive proximity on collaborative innovation (Choi & Contractor, 2019; Fitjar et al., 2016; Květoň et al., 2022; Lauvås & Steinmo, 2021; Simensen & Abbasiharofteh, 2022). However, a controversy exists regarding the two-sided effects of proximities, known as the proximity paradox (Boschma & Frenken, 2010; Broekel & Boschma, 2012). One of the key idea is the notion of optimal cognitive proximity (Cohendet & Llerena, 1997; Nooteboom, 2000). The theoretical insight put forward holds that cognitive proximity both enables and constrains learning (Balland et al., 2020). While cognitive diversity broadens the scope of learning, a certain degree of cognitive proximity is necessary to reduce communication costs (Nooteboom, 2000). Therefore, while much of the existing literature on cognitive proximity has primarily examined its linear effects, some studies have delved into the inverse U-shape effects of proximity and explored the existence of an optimal level of proximity (Broekel & Boschma, 2012; Choi & Contractor, 2019; Guan & Liu, 2016; Martínez Ardila et al., 2020; Nooteboom et al., 2007; Petruzzelli, 2011; Santos et al., 2021; Wuyts et al., 2005; Zhang et al., 2019).

Since the process of knowledge accumulation and diffusion depends on the attributes of underlying technologies in each sector (Dosi & Nelson, 2010; Simensen &

Abbasiharofteh, 2022), the friction of knowledge flow is influenced by the characteristics of the knowledge itself. One of the characteristics of knowledge that affects flow of knowledge itself is ‘knowledge complexity’. Knowledge complexity is the value of knowledge characterized by novelty and inimitability, and more complex knowledge is argued to be a fundamental building block of competitive advantage and economic growth (Balland & Rigby, 2017; Mewes & Broekel, 2022). As complex knowledge is harder to diffuse in space than simple ones, affecting inter-organizational learning process (Balland & Rigby, 2017). Studies on knowledge complexity is mainly on relatedness theory have explored how the similarity between knowledge elements affects the generation of new knowledge within knowledge spaces (Hidalgo et al., 2018; Kogler et al., 2013). However, research on how the proximity of knowledge bases of multiple actors within collaborative spaces, affect collaborative innovation, is still unexplored.

Therefore, this study aims to examine how knowledge complexity moderates the two-sided effect of cognitive proximity on collaborative innovation by empirically analyzing the relationship in the biotechnology sector in the United States between 1982 and 2021. Collaborative innovation and knowledge space is approximated with patent data of USPTO database. The panel regression results confirm the inverse U-shape effect of cognitive proximity on inter-organizational learning and collaboration and the moderation effect of technological complexity.

This study is structured as follows. Chapter 2 presents the theoretical background on proximity theory and knowledge complexity literatures. Chapter 3 provides the empirical settings for analysis including data and methodology. Chapter 4 shows the estimation results. Chapter 5 and 6 discuss and conclude overall finding of the research.

Chapter 2. Theoretical background

2.1 Collaborative knowledge creation and proximity

Proximity is a concept that pertains to the relative position of one entity (e.g., individual, company) in relation to another entity (Zimmermann et al., 2022). The literature on proximity explores how spatial factors influence the dynamics of diverse economic interactions, including migratory and trade flows, knowledge creation and diffusion, and productivity (Caragliu, 2022). In this context, space encompasses not only geographical dimensions but also non-geographical aspects such as collaboration space or knowledge space. Proximity can be understood as the friction imposed by space, which increases the costs associated with knowledge diffusion, thereby influencing the incentives for actors to generate, disseminate, and absorb new knowledge (Caragliu, 2022). Ultimately, the objective is to unravel the black box of proximity mechanisms and gain a deeper understanding of how spatial factors shape economic activities and knowledge dynamics.

As can be seen in Table 1, early proximity literatures start from the notion of co-location and geographical proximity. Globalization of economy and decentralization of policy in 1980s leads to growing interest in regional development strategy (Balland et al., 2020). In regional economic development, it is widely suggested that proximity effects are significant (Torre & Wallet, 2014). Agglomeration economies literatures focused on the economic advantages that firms gain from being located in concentrated areas, including reduced production costs, access to specialized services, etc. (Capello, 2022). Geographical transaction costs caused by geographical distance leads to spatial configurations of various types of economic interaction in inter-firm networks (Karlsson & Stough, 2005; Stimson, 2022). Geographical proximity facilitates exchange of tacit knowledge, explaining the concentration phenomena of innovation activities (Capello & Nijkamp, 2009). Emergence of ICTs caused ‘distance destroying’ effect. However, in spite of ‘distance destroying’ effect, physical proximity still shows its power facilitating tacit knowledge, which is usually transferred through face-to-face exchange (Storper, 1997).

However, many empirical studies witness that proximity based on physical space is neither a sufficient nor a necessary condition for inter-organizational collaboration and learning to take place (Balland et al., 2020; Boschma, 2005). This suggests that geographic proximity alone does not explain why solutions may not always be transferable or why actors in close physical proximity may choose to cooperate or not (Zimmermann et al., 2022). In light of these limitations, researchers have introduced various dimensions of non-geographical proximity since the middle of 1980s for better interpretation of innovation and learning processes (Capello, 2022).

One prominent framework, presented by (Boschma, 2005) , identifies four forms of non-geographical proximity: cognitive, organizational, institutional, and social. Organizational proximity refers to the closeness of actors in organizational culture. It encompasses shared belief system or representation coming from a sense of belonging to same organization (Torre & Rallet, 2005). Organizational proximity facilitating coordination and collaboration within or between organizations by managing knowledge exchanges and reducing transaction costs (Boschma, 2005).

Social proximity, as conceptualized by Boschma (2005), refers to the socially embedded relationships between individuals at a micro-level including factors such as friendship, kinship, and shared experiences. This notion is widely recognized as a fundamental requirement for interactive learning processes. Trust, a significant element in social proximity, is often fostered by close social connections and facilitates knowledge exchange (Nooteboom, 2002).

Institutional proximity refers to how closely organizations operate within the same macro-level institutional framework, which includes shared reward systems, norms, and values. One of the key benefits of institutional proximity is the cultivation of a culture of shared trust. This, in turn, facilitates effective learning and innovation by enabling easier information transmission and fostering communication through a common language. Ultimately, institutional proximity creates a stable and supportive environment that fosters successful interactive learning.

When it comes to inter-organizational learning and knowledge diffusion, cognitive proximity becomes a significant dimension to consider because knowledge diffusion as learning is basically the underlying process of cognitive proximity dynamics.(Balland et al., 2015). Cognitive proximity refers to the extent of overlap in knowledge bases among actors (Boschma, 2005). The presence of shared knowledge enables effective communication between them. However, it's important to note that simply having access to new knowledge does not guarantee the acquisition of new knowledge. Therefore, actors require certain level of absorptive capacity to effectively engage in communication (Cohen & Levinthal, 1990). It is worth mentioning that the configuration of knowledge complementarities between actors evolves over time due to the cumulative learning process (Dosi & Nelson, 1994).

Table 1. A diachronic synthesis in the evolution of proximity concept (Source: Capello, 2022)

Time	Static		Dynamic	
	Theory	Type	Theory	Type
1960s	Agglomeration economies	Spatial		
1970s	Economies of urbanization	Spatial (dichotomous)	Spatial diffusion of innovation	Spatial (continuous)
1980s	Industrial district	Socio-economic	Milieu innovateur	Relational
	Economies of urbanization	Geographical (continuous)	Knowledge spillover	Geographical (dichotomous)
1990s			French school of proximity	Organizational
			Learning region	Institutional
			Regional innovation system	Functional
2000s ~ 10s			Evolutionary economic geography	Cognitive

2.2 Proximity paradox and optimal cognitive proximity

The concept of proximity plays a crucial role in inter-organizational learning and knowledge exchange. However, there exists controversy regarding two-side effect of proximities, so-called proximity paradox (Boschma & Frenken, 2010; Broekel & Boschma, 2012). Certain amount of proximity is required for agents to connect and exchange knowledge, but too much proximity might harm their innovative performance (Broekel & Boschma, 2012). Most notable dimension of proximity presenting paradoxical effect is cognitive proximity, with the notion of 'optimal cognitive distance' (Nooteboom, 2000).

Cognitive proximity concept is closely related to the notion of learning, absorptive capacity and combinatory innovation. In resource base view, organizations' resources for knowledge sourcing is limited, therefore their ability to collaborate and seek for external source of knowledge becomes crucial (Broekel & Boschma, 2012). This ability, so-called absorptive capacity, is based on the existing organizational knowledge base, because prior related knowledge facilitates recognizing, assimilating, and applying of new knowledge (Cohen & Levinthal, 1990). Therefore, certain level of proximity between actors' knowledge base is needed to enable acquisition of knowledge in learning process (Boschma, 2005; Nooteboom, 2000). However, in terms of combining nature of innovation, diversity plays important role in knowledge creation and learning. To secure novelty of knowledge, cognitive differences are crucial for complementary partnership. As Nooteboom stated, information is only valuable if it is new but still understandable (Nooteboom, 2000). As both compatibility and diversity of organizational knowledge base are needed for successful learning, there exists optimal level of cognitive distance that allows organizations to maximize the learning benefits from one another (Balland et al., 2020; Boschma, 2005; Nooteboom, 2000).

On the relation between cognitive distance and innovation performance, Nooteboom proposed that there is an inverted-U shaped relationship (Nooteboom et al., 2007). He presented mathematical model, explaining the effect of cognitive proximity on learning as the product of a line representing absorptive capacity effect and novelty effect as visualized in Figure 1. On one hand, absorptive effect shows positive slope line as cognitive proximity increases, and on the other hand, novelty effect shows negative slope because as actors get cognitively close novelty of knowledge decreases. In turn, the learning curve follows this inverted U-shape due to the combined effects of absorptive and novelty effects.

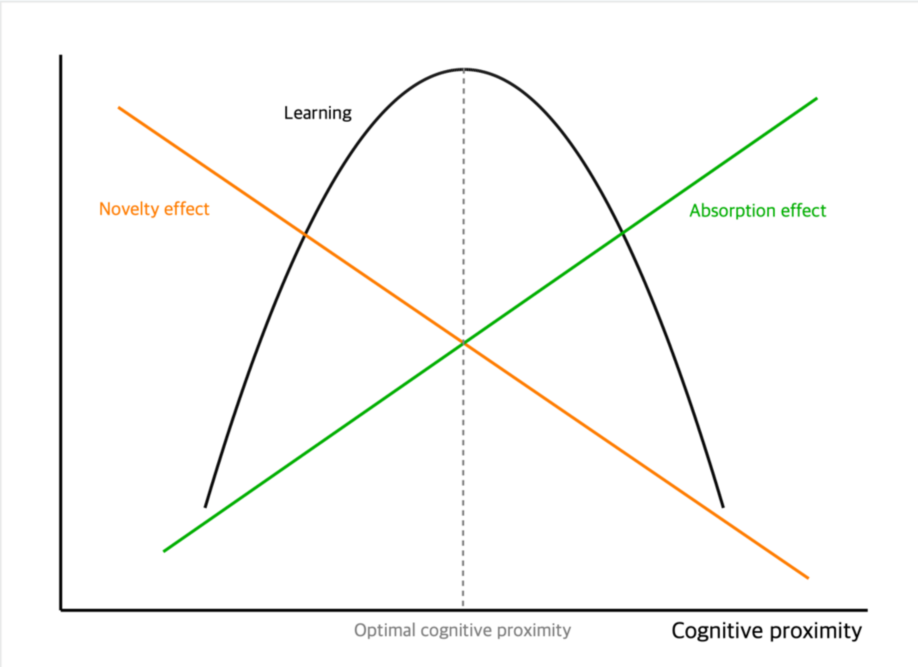

Figure 1. Optimal cognitive proximity (Source: adapted from Nooteboom et al., 2007, p. 1018)

Various studies that explore the impact of cognitive proximity on knowledge and innovative performance and the presence of the optimal cognitive proximity is illustrated in Table 2. Martínez Ardila et al. (2020) investigated joint patents in biotechnological sector in 2012 and confirmed positive quadratic relationship of cognitive proximity. Broekel & Boschma (2012) tested proximity paradox empirically in Dutch aviation industry based on interview conducted in late 2008 and early 2009. The proximity paradox was observed for cognitive and organizational proximity, with a positive impact on cooperation but a negative or no effect on innovative performance. However, the proximity paradox did not hold for geographical and social proximity, as both were found to contribute to network formation and enhance innovative performance.

Interaction of cognitive and geographical proximity in regional university-industry collaboration network in Brazil is investigated by Santos et al. (2021).

While studies introduced above focused on single point in time, there have been studies focusing on more dynamic perspective of cognitive proximity and collaboration. Petruzzelli (2011) focused on university-industry joint patent in European countries, and Wuyts et al. (2005) analyzed interfirm agreements in pharmaceutical, biotech and ICT industries. Exploitative and exploratory innovations in patent collaboration network in nano-energy field are explored by Guan & Liu (2016). Optimal cognitive proximity has been confirmed in several empirical studies on knowledge transfer in case of mergers and acquisitions (Ahuja & Katila, 2001; Cloodt et al., 2006).

Several studies explored the factors affecting optimal cognitive proximity. Nooteboom et al. (2007) explored R&D collaboration between 116 companies over 12-year period from 1986 to 1997. In addition to confirmation of an inverted U-shaped effect of cognitive distance on innovation performance of firms, authors stressed mixed moderation effect of cumulative technical capital.

Zhang et al. (2019) investigated how the effect of recombination distance on recombinant innovation is moderated by network structural governance and relation governance. They showed that the inverted U-shape effect of recombinant distance becomes steeper when structural holes are spanned by focal firm or when alliance partners have lower private-public ratio.

Choi & Contractor (2019) focus on strategic alliances of biopharmaceutical industry between 2000 and 2004. Authors find that appropriate level of the overall degree of coordination and communication leads to better R&D alliance performance. Moderation effect of organizational diversity and technological base diversity is explored, but technological base diversity does not show significant effect as degree of coordination is measured in context of task interactions.

Still, empirical evidence dealing with determinants of optimal cognitive proximity is lacking, in contrast to the detection of inverse U-shape.

Table 2. Studies exploring inverse U-shape of cognitive proximity

	Only inverse U-shape	**Moderation effect**
Single year	Martínez Ardila et al. (2020) Broekel & Boschma (2012)	Santos et al. (2021)
Various time period	Petruzzelli (2011) Wuyts et al. (2005) Guan & Liu (2016) Ahuja & Katila (2001) Cloodt et al. (2006)	Nooteboom et al. (2007) Zhang et al. (2019) Choi & Contractor (2019)

2.3 Knowledge complexity

Knowledge plays a crucial role in explaining the uneven development of regions, particularly in terms of economic growth and competitiveness (Solow, 1956; Nelson & Winter, 1982; Romer, 1990; Balland & Rigby, 2017). As the world becomes increasingly globalized, the importance of knowledge as a critical input in production has further amplified, with the ability to generate new knowledge emerging as a key driver of competitive advantage (Porter, 1985). The generation of new knowledge primarily stems from the recombination of existing knowledge, thereby making the existing knowledge base of a region a fundamental determinant of its innovation capacity (Boschma & Lambooy, 1999).

Consequently, the disparity in economic development among regions ultimately hinges upon the knowledge they possess, giving rise to the concept of a knowledge-based region. Earlier researches have focused on the quantity of knowledge, considering individual patents as homogenous. However, both the quantity and quality of knowledge held by a region exert significant influences on its developmental trajectory(Balland & Rigby, 2017). It is important to recognize that not all knowledge is equal; regions endowed with more novel and valuable knowledge inherently possess a greater competitive advantage (Maskell & Malmberg, 1999). The difference in novelty and value of inventions has long been widely acknowledged and numerous studies have sought to develop indicators to evaluate the quality of inventions. Trajtenberg (1990) used forward citation to measure the quality of individual patents, and Lanjouw and Schankerman (2004) proposed composite quality index with four patent indicators - numbers of claims, forward citations, backward citations, and patent family size. Although patent valuations provide one indicator of the value of knowledge held by firms and located in different regions, another critical dimension of the competitive advantage conveyed by knowledge is its inimitability (Balland & Rigby, 2017).

This raises the fundamental question of what kind of knowledge is challenging to replicate. Knowledge is known to be spatially sticky (Asheim & Isaksen, 2002).

However, not all knowledge is. Some features contribute to this challenge, including the high cost associated with acquiring new knowledge, the implicit or complex nature of knowledge itself, and the substantial costs involved in assimilating and absorbing it effectively (Balland & Rigby, 2017). Therefore, high-value, non-ubiquitous, complex and tacit knowledge is hard to copy (Maskell & Malmberg, 1999). On the other hand, knowledge with more routinized form tend to be easier to move over space (Balland & Rigby, 2017).

Then, which regions possess more valuable and harder-to-replicate knowledge? To address this, Fleming & Sorenson (2001) proposed a search-based, recombinant innovation model, utilizing data from the United States Patent and Trademark Office (USPTO) to develop indicators that estimate the level of difficulty in combining distinct knowledge subsets within each patent. Another approach, introduced by Hidalgo & Hausmann (2009), involves measuring complexity through the diversity of products at a national level, drawing on the concept of the product space. Building upon this, Balland & Rigby (2017) defined knowledge complexity as "the kinds of knowledge are more difficult to develop or to replicate than others" and argued that cities characterized by more complex technological configurations tend to generate knowledge that is inherently more difficult to replicate. They constructed city-technology knowledge networks to propose the notion of Knowledge Complexity Index (KCI) and adopted the method of reflection, as outlined in Hidalgo and Hausmann's work. KCI encompasses two key variables: city diversity, capturing the breadth of knowledge domains within a city, and technology ubiquity, reflecting the extent to which specific technologies are pervasive across cities. In this research the method of Balland & Rigby (2017) is chosen.

Broekel (2019) proposed more network-based measure of knowledge complexity called structural diversity. Structural diversity represents the diversity of (subnetwork) topologies in technologies' combinatorial networks and it is based on the concept of Network Diversity Score (NDS) developed by Emmert-Streib & Dehmer (2012) .

Knowledge complexity, characterized by novelty and inimitability, affects the flow of knowledge and inter-organizational learning. Balland & Rigby (2017)show that complex knowledge tends to be produced in few regions and not easy to be diffused. Mewes & Broekel (2022) stated as follows:

> *"... since complex technologies entail more information, they are more difficult to learn, and to copy limiting their diffusion."*

However, the effect of knowledge complexity on inter-organizational learning and cognitive proximity is not explored. Therefore, this study aims to investigate complex dynamics of cognitive proximity, inter-organizational learning, and knowledge complexity.

Chapter 3. Data and methodology

3.1 Empirical context: US biotechnology sector

Biotechnology is defined as ‘the application of science and technology to living organisms, as well as parts, products and models thereof, to alter living or nonliving materials for the production of knowledge, goods and services’ (OECD 2005). It encompasses scientific and industrial fields that aim to comprehend and manipulate living or biologically-active substances at the molecular level, often utilizing DNA techniques and genetic information analysis (*Patent Expert Issues: Biotechnology*, 2023). The application of modern biotechnology is anticipated to bring significant advancements in various domains, including healthcare, pharmaceuticals, energy generation, textiles, chemicals, plastic, paper, fuel, food processing, and environmental preservation. (*Biotechnology*, 2023; *Patent Expert Issues: Biotechnology*, 2023).

Biotechnology offers technological solutions for many of the health and resource-based problems facing the world, leading to the concept of “bioeconomy” (OECD, 2009). In recent years, biotechnology has gained substantial attention from governments, research institutions, and industries around the world. The European Commission has emphasized the importance of biotechnology as a key driver of innovation and competitiveness in Europe . Additionally, the role of biotechnology in achieving sustainable development goals and addressing global health issues is also acknowledged (Jorgensen, 2017).

Biotechnology is one of the most competitive and intensive in knowledge in the global economy (Martínez Ardila et al., 2020). This sector is highly driven by innovative technologies and methodologies in other fields of science such as computing, data sciences, and the recent emergence of machine learning and artificial intelligence (Philp & Winickoff, 2019). These knowledge intensive and complex aspect of biotechnology make it suitable for analyzing potential impact of knowledge complexity in innovation network. Due to the complex and interdisciplinary nature of the field, collaborative efforts between academia, industry, and research institutions across different countries has facilitated knowledge exchange and cross-disciplinary research in biotechnology (OECD, 2009). The most well-known is the Human Genome Project, a public-private sector collaborative effort that sequenced the entire human genome two years ahead of schedule in 2003, after 13 years of work (OECD, 2009). The importance of establishing and innovation ecosystem for technological advancement in biotechnology is stressed by Philp & Winickoff (2019).

The United States is a prominent country in the field of biotechnology, with a substantial share of biotechnology-related patents, among OECD countries. Especially, advances in genetic engineering approaches and DNA sequencing technologies over four and a half decades have accelerated innovation significantly in the United States (Philp & Winickoff, 2019). Moreover, biotechnology-related fields occupy the top three positions of US national research and development (R&D) expenditure, which has been steadily increasing since the 1970s. Therefore, US provides ample opportunities to explore interactions among diverse institutions without neglecting cross-national heterogeneity.

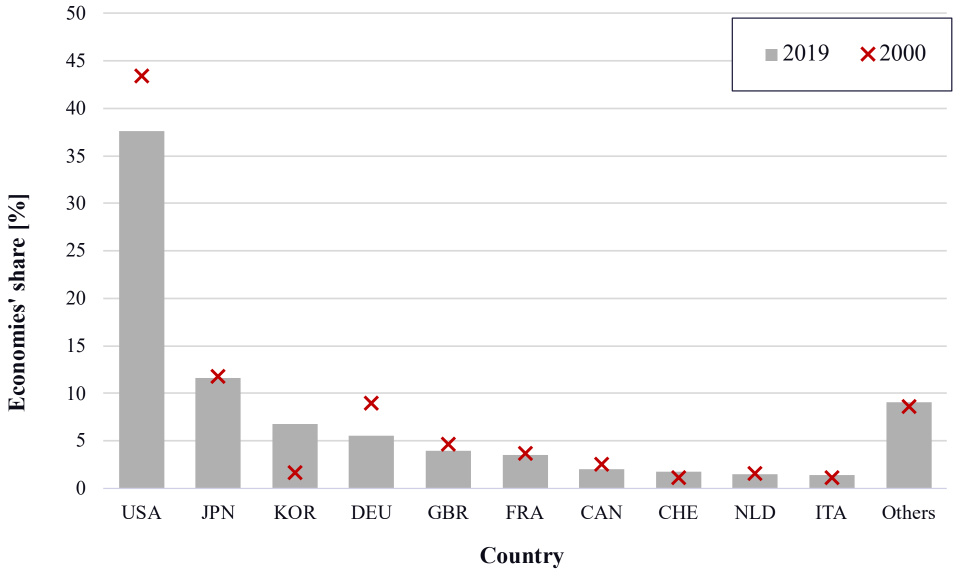

Figure 2. Economies' share in biotechnology-related patents, OECD countries (Source : OECD, 2022)

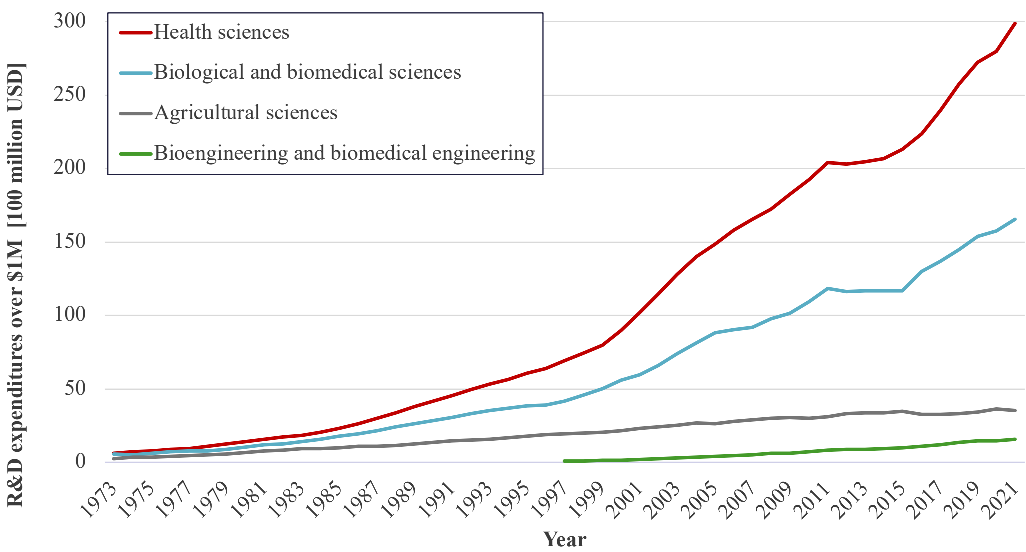

Figure 3. R&D Expenditures for institutions with over $1M (Source : NCSES, 2023)

Table 3. R&D Expenditures for Institutions With Over $1M in US, 2021, top 15 of 43 fields, Source : NCSES, 2023

No.	Field of study	R&D expenditures [$1,000]
1	Health sciences	29,884,728
2	Biological and biomedical sciences	16,557,201
3	Agricultural sciences	3,548,896
4	Electrical and communications engineering	3,080,363
5	Computer and information sciences	2,951,923
6	Physics	2,463,331
7	Other engineering	2,397,439
8	Chemistry	1,999,546
9	Mechanical engineering	1,881,551
10	Education	1,616,705
11	Bioengineering and biomedical engineering	1,560,381
12	Civil engineering	1,482,377
13	Aerospace engineering	1,451,964
14	Other life sciences	1,439,006
15	Psychology	1,326,030

3.2 Data

To empirically analyze this relationship, the biotechnology sector in the United States will be investigated using patent network data from 1982 to 2021. For data, patent data of biotechnology field is extracted from United States Patent and Trademark Office(USPTO)(USPTO, 2023). Collaboration is measured with patent co-authorship network at organizational level. Bunch of literatures dealing with knowledge network and collaboration utilize patent data to measure collaboration between actors. Despite having certain drawbacks, patents are extensively employed in empirical studies on technological knowledge creation due to their unique ability to offer detailed information on technological knowledge (Griliches, 1990). Patents are often favored as the primary large-scale data source in this context (Mewes & Broekel, 2022). To construct panel dataset, patents relevant in biotechnology sector is identified by selecting patents including ipc codes belong to “Biotechnology” in WIPO’s IPC concordance table (WIPO, 2023). The period of 1982 to 2021 is concerned. Individual assignees and non-US assignees are removed, and only collaboration between US assignees is considered. As collaboration is under interest, only patents co-applied by organizations in US is considered, which results in a total of 14,353 patents and 1,766 assignees.

Table 4. Descriptive statistics

Dimensions	Value
Number of patents	14,353
Period	1982-2021
Number of organizations	1,766
Patents per organization	2.33
Organizations per patent	2.12

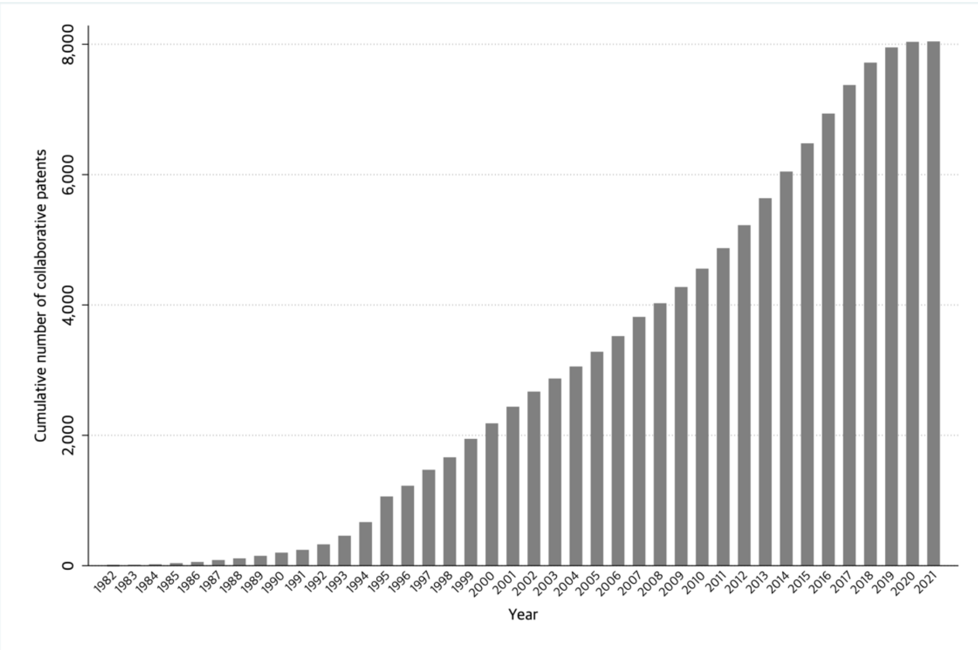

Figure 4. Number of collaborative patents yearly

3.3 Variables

3.3.1 Dependent variables

This study aims to focus on bilateral relationships rather than full networks, panel data with pairwise observation is constructed based on this dataset. Collaborative innovation is measured by the number of co-patents between actors. Maximum value of LINK is 68, and mean value is 0.454.

3.3.2 Explanatory variables

Cognitive proximity is measured by Jaccard similarity of actors' ipc code portfolio at time t. It is defined as follows:

$$COG_{ij,t} = \frac{|IPC_{i,t} \cap IPC_{j,t}|}{|IPC_{i,t} \cup IPC_{j,t}|} \qquad \text{Eq. (1)}$$

Here $IPC_{i,t}$ and $IPC_{j,t}$ refers to two vectors including 4-digit ipc codes of patents each organization applied in period t. The cognitive proximity ranges from zero to one. If ipc portfolios of two organizations are same, COG have value of 1, and if there's no sharing ipc codes between organizations COG is zero.

Knowledge complexity is measured on the knowledge that is conveyed between actors, not about the knowledge base of each actor. Here variable KC indicates mean knowledge complexity of ipc codes appearing in co-patents in time t. To measure knowledge complexity of each ipc codes, methods of reflection from Balland & Rigby (2017) is followed. Knowledge complexity is based on the configuration of actor-knowledge network, among those that exhibits Relative Technological Advantage (RTA) (Balland & Rigby, 2017).

RTA is measure of whether an organization's share of knowledge k in organization's knowledge portfolio is larger than the share of knowledge k in entire population. Usually, $RTA_{i,k,t}$ = 1 if RTA is higher than 1 and 0 if not.

$$\frac{patents_{i,k,t} / \sum_k patents_{i,k,t}}{\sum_i patents_{i,k,t} / \sum_i \sum_k patents_{i,k,t}} \qquad \text{Eq. (2)}$$

Based on RTA, bipartite network M is constructed where $M_{i,k} = RTA_{i,k}$ of orgnization i on knowledge k. Following the method of reflections, two variables - the diversity of cities and the ubiquity of technological classes - based on bipartite network M are recursively combined.

$$DIVERSITY = K_{i,0} = \sum_k M_{i,k} \qquad \text{Eq. (3)}$$

$$UBIQUITY = K_{k,0} = \sum_i M_{i,k} \qquad \text{Eq. (4)}$$

After n interactions of sequentially combining two equations, KCI of each knowledge is obtained.

$$KCI_k = K_{k,n} = \frac{1}{K_{k,0}} \sum_k M_{i,k} K_{i,n-1} \qquad \text{Eq. (5)}$$

In this study the 19 iteration steps are conducted to obtain KCI. This measure is fundamentally relative, because it is a measure of inimitability. Therefore, knowledge complexity of each ipc codes differs at every time period.

3.3.3 Control variables

Social proximity is measured by natural logarithm of the number of co-patents in last two period. As social proximity indicates the extent of mutual relationship and trust between actors, previous collaboration is measured. To avoid endogeneity issue in fixed effect model, natural logarithm is applied.

$$SOC_{ij,t} = ln\left(LINK_{ij,t-1} + LINK_{ij,t-2}\right) \quad \text{Eq. (6)}$$

Geographical proximity is measured by the inverse of the inverse of the natural logarithm of the physical distance. The shortest distance between two points on a global ellipsoid (WGS84 ellipsoid) is computed for absolute physical distance. (C.F.F. Karney, 2013) Absolute distance ranges from 0 to 14879.58 km. To convert distance to proximity measure, log of distance is inversed.

$$GEO_{ij} = \frac{1}{ln\left(dist_{ij} + 1\right)} \quad \text{Eq. (7)}$$

Institutional proximity measures whether two organizations are in same institutional background. Institutional background is categorized into two, private or public sector. This study follows binary measure of previous studies, equal to 1 if two organizations are in same sector and 0 if not.

To control heterogeneity of actors, the experience of organizations is measured by the number of periods each organization appeared in the collaboration network. As all variables are measured in dyad level, mean of experience of each actor in pair is calculated. Natural logarithm of the number of inventors is used as the size of the organization. Mean value is also calculated for dyad value.

Table 5. Descriptive statistics of variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
LINK	22,071	.454	1.331	0	68
COG	22,071	.048	1.008	-1.072	3.423
KC	22,071	.07	1.066	-.457	2.667
SOC	22,071	.377	.514	0	4.836
GEO	22,071	.248	.25	.104	1.103
INST	22,071	.898	.303	0	1
EXPR	22,071	5.737	2.684	0	12
SIZE	22,071	6.871	1.49	.916	10.56

3.4 Mathematical specification

3.4.1 Econometric specification

The hypothesis can be specified in mathematical forms. Mathematical specification follows that of Nooteboom et al.(2007). Novelty value (N) shows downward sloping line:

$$N = a_0 - a_1 P, \qquad a_0, a_1 > 0 \qquad \text{Eq. (8)}$$

As cognitive proximity (P) increases, which means when actors become cognitively closer, novelty effect decreases. In this study novelty effect is assumed to be largely exogenous, following Nooteboom et al.(2007). Absorptive capacity (A) shows upward sloping line:

$$A = b_0 + b_1 P\,, \quad b_0, b_1 > 0 \qquad \text{Eq. (9)}$$

As cognitive proximity increases, absorption effect increases. Here we focus on the absorption effect. To specify the effect of knowledge complexity (KC), it is assumed that higher KC weakens absorption effect, thus shifting the line downward.

$$A = b_0 + (b_1 + KC)P,\ \ b_0, b_1 > 0 \qquad \text{Eq. (10)}$$

Multiplying (8) and (10) results in collaborative innovation (L) of the pair of actors.

$$L = A * N = a_0 b_0 + (a_0 b_1 - a_1 b_0)P + a_0 KC * P - a_1 KC * P^2 - a_1 b_1 P^2 \qquad \text{Eq. (11)}$$

Equation (11) specifies the basic model to be used for an econometric test.

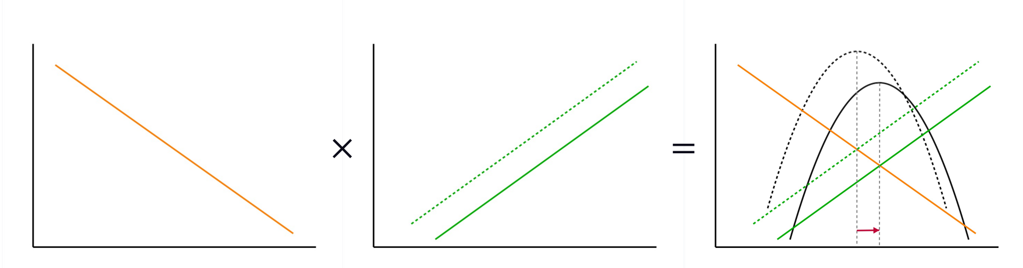

Figure 5. Visualization of mathematical specification

3.4.2 Detecting inverted U-shape

To identify inverted U-shape relations, this study follows methodology of Lind & Mehlum, (2010). Given the specification Eq. (11), it can be generalized into estimation form like follows:

$$L = \beta_0 + \beta_1 P + \beta_2 P^2 + \beta_3 P\mathrm{KC} + \beta_4 P^2 KC + \beta_5 KC \qquad \text{Eq. (12)}$$

Two standard one-side test is conducted for lower and upper bound. Hypothesis for inverted U-shape is like followed:

$$\begin{aligned} &H_0^L: \beta_1 + \beta_2\, f'(x_l) \leq 0 vs. H_1^L: \beta_1 + \beta_2\, f'(x_l) > 0, \\ &H_0^H: \beta_1 + \beta_2 f'(x_h) \geq 0 vs. H_1^H: \beta_1 + \beta_2\, f'(x_h) < 0. \end{aligned} \qquad \text{Eq. (13)}$$

The presence of inverse U-shape implies $\beta_1 + 2\beta_2 x_l > 0$ and $\beta_1 + 2\beta_2 x_h < 0$.

3.4.3 Checking moderation effect of inverted U-shape

To identify the moderation effect on inverted U-shape relations, this study follows methodology of Haans et al. 2013. Give Eq. (12), the first order condition is as follows:

$$\frac{\partial L}{\partial P} = \beta_1 + 2\beta_2 P + \beta_3 KC + 2\beta_4 P * KC \qquad \text{Eq. (14)}$$

Deriving P which yields the turning point,

$$P^* = \frac{-\beta_1 - \beta_3 KC}{2\beta_2 + 2\beta_4 KC} \qquad \text{Eq. (15)}$$

To figure out how turning point P^* changes as TC changes, we takederivative with respective to TC.

$$\frac{\partial P^*}{\partial KC} = \frac{\beta_1\beta_4 - \beta_2\beta_3}{2(\beta_2 + \beta_4 KC)^2} \qquad \text{Eq. (16)}$$

As the denominator is strictly larger than zero, the direction of shift depends on the sign of numerator.

Therefore, when $\beta_1\beta_4 - \beta_2\beta_3$is positive, turning point P* will move right as TC increases.

Chapter 4. Estimation result

4.1 Estimation model

The estimation model used in this study is a panel negative binomial regression with fixed effects. The dependent variable (DV) is a count variable with only non-negative values, which makes the negative binomial regression suitable. The fixed effects are tested using the Hausman test. The estimation equation is specified as follows:

$$LINK_{i,t} = \beta_0 + \beta_1 COG_{i,t-1} + \beta_2 COG_{i,t-1}^2 + \beta_3 COG_{i,t-1} * KC_{i,t-1} + \beta_4 COG_{i,t-1}^2 * KC_{i,t-1} + \beta_5 KC_{i,t-1} + Control_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t} \quad \text{Eq. (17)}$$

The equation follows the mathematical specification outlined earlier, incorporating time lags for causal analysis.

Three variations of the model are constructed: (1) Base model (model 1), (2) Model 2 with added time-variant control variables, and (3) Model 3 with added time-consistent control variables.

4.2 Estimation result and Hypothesis testing

The estimation results are shown in Table 3. The hypothesis is tested following previous section 3.3.2 & 3.3.3. The coefficient of the square term (β_2) is significant and value of -0.957, which is negative, satisfying the conditions for an inverse U-shape. The extreme point is 0.089 and falls within the range of the COG (-1.072 ~ 3.423). The slopes at the lower and upper bounds have significant signs. Therefore, the detection of an inverse U-shape is confirmed.

Table 6. Estimation results

	(1)	(2)	(3)	(4)
COG		.3124***	.1772***	.1708***
		(.0274)	(.0268)	(.0269)
COG^2		-.0449***	-.1057***	-.0957***
		(.0153)	(.0157)	(.0157)
COG*KC		.1268***	.1001***	.1096***
		(.0279)	(.0242)	(.0241)
COG^2 * KC		-.0673***	-.0303**	-.0354***
		(.0134)	(.0121)	(.0121)
KC		-.1452***	-.2186***	-.2185***
		(.0189)	(.0183)	(.0181)
SOC	-.1193***		.0665**	.0903***
	(.0241)		(.0306)	(.0309)
GEO	-1.2473***			-1.2669***
	(.1633)			(.1681)
INST	-.3753**			-.4416**
	(.1741)			(.1802)
EXPR	-.4571***		-.4693***	-.4796***
	(.0082)		(.0084)	(.0086)
SIZE	.0195			-.0136
	(.0649)			(.0673)
Const	3.7221***	.3006***	3.1491***	4.1331***
	(.6053)	(.058)	(.0677)	(.6295)
Obs.	21,758	21,758	21,758	21,758
Net effect	*na*	.3168	.1736	.1689
Log likelihood	-8311.75	-10624.61	-8245.53	-8204.77

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

The derivative of the optimal point (P^*) is significantly different from zero, indicating a significant shift in the optimal point. Additionally, the product of the coefficients ($\beta_1\beta_4 - \beta_2\beta_3$) is positive, satisfying the condition for a positive sign of the derivative of the optimal point. This confirms the moderation effect of KC on the inverse U-shape of COG.

Table 7. Test result of detecting inverted U-shape

	Lower bound	**Upper bound**
Interval	-1.072	3.423
Slope	2.223	-6.383
t-value	6.260	-6.013
P>|t|	1.96e-10	9.23e-10

4.3 Predicted margin and marginal effects

Based on the regression results, the predicted margins of COG can be visualized (Figure 4). In the visualization, the blue line represents the predicted values of COG when KC is at its minimum, the green line represents the predicted values when KC is at its maximum, and the red line represents the predicted values when KC is at the midpoint between the minimum and maximum values.

The graph shows a clear rightward shift of the optimal point as KC increases. This aligns with the hypothesis that cognitive proximity becomes more important in achieving optimal collaboration performance when disseminating and learning more complex knowledge. The absorption effect graph also indicates a downward shift, supporting the assumption made in this study that the absorption effect moved downward. Therefore, the moderation effect of KC on COG weakened the absorption effect.

Another notable finding is that the curvature of the graph steepens as KC increases. This is evident from the average marginal effect graph (Figure 5). The steeper slope of the marginal effect indicates that COG becomes more sensitive to changes in complex knowledge. This suggests that finding collaboration partners becomes more challenging in complex knowledge domains, as slight variations in cognitive proximity have a significant impact on collaboration performance. This phenomenon is attributed to the co-evolving dynamics of cognitive proximity, where collaboration increases cognitive proximity. Therefore, dynamic cognitive proximity makes organizations harder to find collaboration partners in complex knowledge domains.

In sum, the overall results support the presence of an inverse U shape, indicating that moderate levels of cognitive proximity are associated with higher levels of inter-organizational learning. The moderation effect of knowledge complexity was significant, indicating that complex knowledge is more difficult to absorb and collaborate on. The study also found that the marginal utility of cognitive proximity becomes more pronounced with greater knowledge complexity.

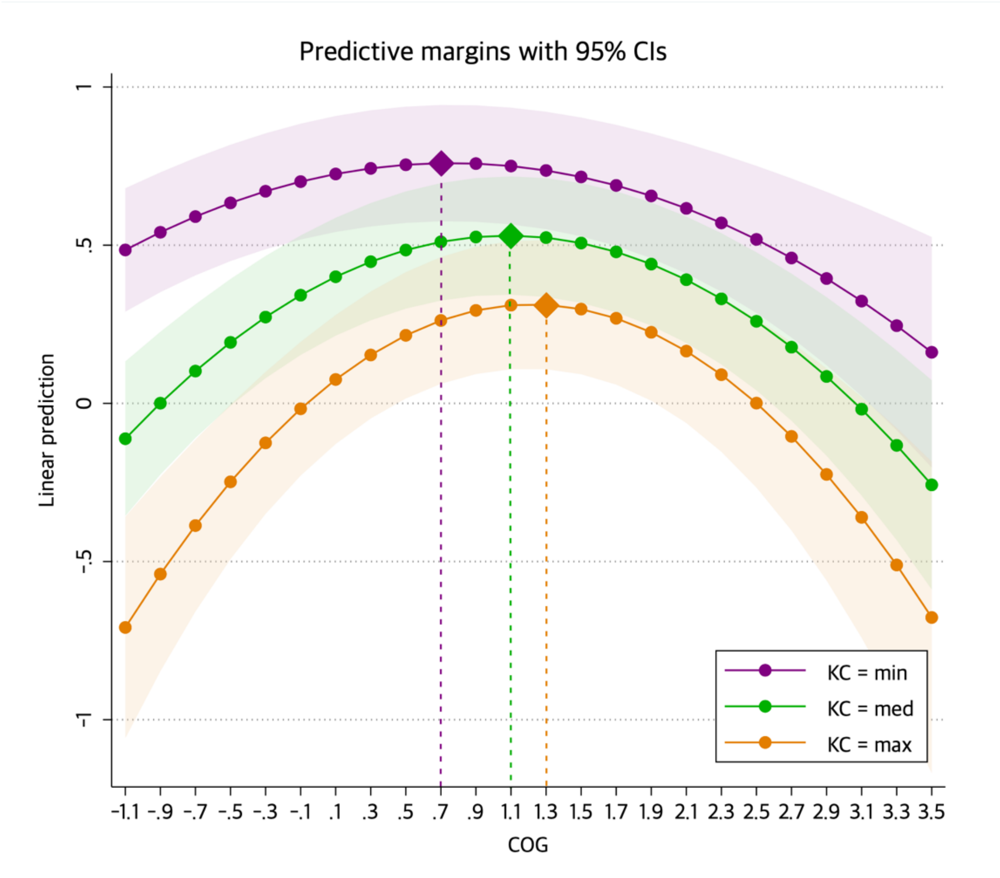

Figure 6. Predictive margin of COG for different level of KC

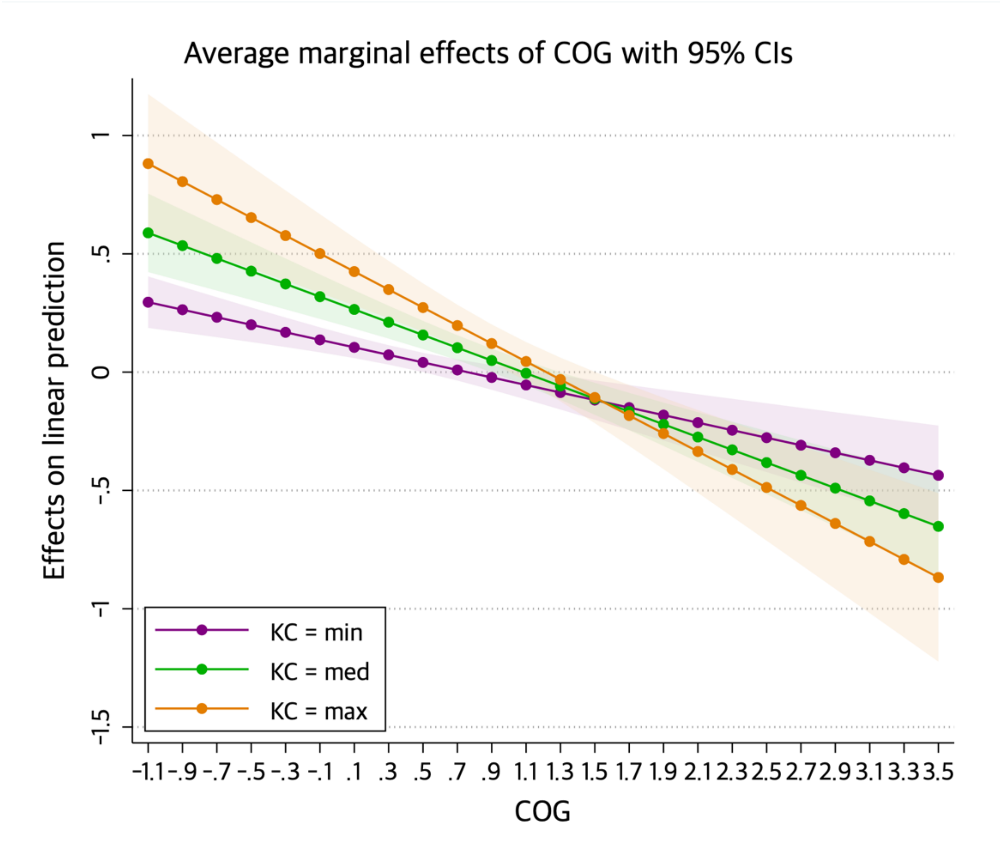

Figure 7. Average marginal effects of COG for different level of KC

4.4 Robustness check

In order to show the robustness of the model, two additional analyses were performed. Firstly, to address concerns about false-positive results, a modified model was estimated by including a variable representing cognitive proximity as a categorical variable with values ranging from 1 to 4 based on quantiles. Secondly, a panel logit model was employed as an additional approach to validate the results. The results of these alternative model confirmed the robustness of the findings. The detailed results of this robustness check can be found in the appendix.

Chapter 5. Discussion

The analysis results confirmed a clear inverse U-shaped effect of cognitive proximity on the dependent variable, aligning with previous research findings. Organizations with low cognitive proximity tend to have disparate knowledge base, sharing few common knowledge. Collaboration between them can offer great chance to obtain novel knowledge from each other which expands organization's knowledge base and becomes the source for innovation. However, obtaining new knowledge is much difficult when it comes from unfamiliar field. Thus, too low cognitive proximity causes reduced learning outcomes.

On the other hand, organizations with high cognitive proximity have an increased ability to understand each other's knowledge. There exists higher potential for knowledge acquisition through collaboration. However, for each organization to benefit from collaboration, there should be complementary knowledge. Similar knowledge base between organizations lead to higher possibility that I possess the knowledge that the other party has. This increases the possibility of the other party becoming a competitor rather than a collaborator and reduces the potential synergy that can be obtained through collaboration. Therefore, excessively high cognitive proximity also leads to lower collaborative outcomes. Consequently, it is important to seek collaboration partners with an appropriate level of cognitive proximity to achieve optimal collaborative outcomes.

Furthermore, two-way moderation effect of knowledge complexity on the proximity effect is confirmed. First, the optimal level of cognitive proximity increases with higher level of knowledge complexity, which shows positive moderating effect of complexity on the proximity effect on collaborative innovation. Complex technologies require higher cognitive proximity for effective collaboration. This is due to the difficulty in diffusing complex knowledge. Complex knowledge has tacit and nuanced characteristics, making its diffusion challenging. Therefore, organizations achieve higher collaborative performance when engaging in communication with closer cognitive proximity, as complex knowledge is inherently difficult to disseminate.

There also exists downward shift of the optimal point aligns with the hypothesis of the negative impact of knowledge complexity on the absorption effect. Even at the optimal cognitive proximity, complex knowledge exhibits lower learning outcomes compared to less complex knowledge. This is because complex knowledge is challenging to diffuse during inter-organizational collaboration, resulting in relatively lower learning performance.

Secondly, the marginal effect of cognitive proximity also increases in complex fields, indicating that proximity plays stronger role as knowledge complexity increases. This suggests that learning outcomes are more sensitive to cognitive proximity in complex domains, where even small differences in cognitive proximity can lead to significant differences in learning outcomes. In specialized domains, knowledge is often narrow in scope, making it easy to deviate from the domain's boundaries with slight cognitive proximity changes. Moreover, the acquisition of new knowledge decreases rapidly as the domain is narrow. Therefore, a precise alignment of proximity between collaboration partners becomes more crucial in complex knowledge fields.

Furthermore, this steep slope near the optimal proximity implies that long-term collaboration is much harder. Due to dynamic nature of collaboration process, common knowledge increases through learning therefore reducing complementary knowledge between partners. In long-term, proximity between partners become closer as time passes. As a result, organizations move away from the optimal distance, diminishing their performance as collaboration continues. Therefore, organizations find it challenging to identify optimal partners for achieving the best collaborative outcomes in complex knowledge domains.

Overall, these findings emphasize the importance of considering both cognitive proximity and the characteristics of knowledge in collaborative innovation. Organizations need to carefully assess the level of cognitive proximity and knowledge complexity to form effective partnerships and maximize collaborative performance.

Chapter 6. Conclusion

6.1 Research summary

The study explores the role of cognitive proximity in collaborative innovation and the moderating effect of knowledge complexity on the relationship between cognitive proximity and collaboration. The empirical analysis utilizes USPTO patent data from 1982 to 2021 within the biotechnology sector of United States.

The estimation results confirm the presence of an inverted U shape, indicating that appropriate level of cognitive proximity enhance inter-organizational learning. The two-way moderation effect of knowledge complexity was also significant. Firstly, the optimal cognitive proximity increases as knowledge complexity increases, implicating that organizations need to be cognitively closer for successful learning due to weakened absorption effect.

Secondly, the marginal effect of proximity is also moderated by knowledge complexity. As knowledge become more complex, the slope of U-shape gets steeper. This indicates that the impact of cognitive proximity becomes more pronounced with higher knowledge complexity and an alignment of proximity in collaboration becomes more crucial in complex knowledge fields. This result also implies that in long-term, it is much harder for organizations in complex industry to maintain partnership with single partner.

In summary, organizations sharing complex knowledge can achieve optimal collaboration performance by partnering with cognitively close partners. Also, the importance of cognitive proximity is more pronounce in more complex fields. The findings emphasize the intricate relationship between cognitive proximity, knowledge complexity, and the absorptive capacity of inter-organizational learning.

6.2 Implications

This study has several significant implications. Firstly, this study contributes to the academic literature by offering a more comprehensive understanding of cognitive proximity dynamics. It challenges the simplistic linear models that have been commonly used in previous studies on proximity and emphasizes the importance of considering the two-sided nature of cognitive proximity. Previous research has primarily focused on modeling simple linear relationships, failing to fully capture the intricate dynamics of cognitive proximity. In contrast, the present study delves into the intricate dynamics of cognitive proximity, taking into account the moderating effect of knowledge complexity. By considering the intricate interplay between individuals' cognitive proximities, this research offers valuable insights into the collaboration strategies that can be employed by organizations.

Secondly, the research provides valuable insights into collaboration strategies that organizations can employ by examining the interplay of cognitive proximities. It highlights the significance of finding collaborative partners who can effectively maximize collaborative performance, particularly in complex technology domains. By understanding and leveraging cognitive proximity, organizations can enhance their collaborative efforts and achieve better outcomes. This suggests that organizations should carefully select partners who possess specialized knowledge and expertise in order to enhance their collaborative endeavors. Moreover, to overcome cognitive distance between organizational knowledge base, they can improve absorptive capacity by investing more on explorative R&D or constructing easier institution for external collaboration, when collaborating in complex fields. In terms of the duration of the collaboration organizations should expect short-term collaboration and seek for potential partner more often in more complex field.

Furthermore, the study offers insights for formulating policies aimed at fostering innovation networks. It suggests that encouraging collaboration among actors specializing in the same field, rather than excessively diverse fields, may be more effective in establishing complex technology clusters or networks. Moreover, the overall period of project should be not so long because as time passes each actor in cluster will become similar, lowering innovation performance. This finding can guide policymakers and stakeholders in designing strategies to create supportive ecosystems for innovation and facilitate technology transfer.

6.3 Limitations and future research suggestions

One limitation of the study is that this study focused on examining cognitive proximity and knowledge complexity within the biotechnology sector. Future research should adopt more sectoral perspective that encompasses a broader range of industries to generalized the impact of knowledge complexity on cognitive proximity.

Also, moderation effect of knowledge complexity in other forms of proximity will be interesting for future research. Analyzing other types of proximity will bring broader understanding of proximity mechanism.

Additionally, exploring organizational heterogeneity more extensively will provide more policy-side implication. Specific type of interactions such as university-industry collaboration or triple helix relations will provide more comprehensive understanding of how cognitive proximity and knowledge complexity manifest in different contexts. By incorporating these perspectives, further research can yield valuable insights with policy implications in facilitate technology transfer, and create supportive ecosystems for innovation.

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Appendix 1: Matrix of correlations between variables

[1.1] Matrix of correlations between variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) COG	1.0000							
(2) COG_alt	0.9450	1.0000						
(3) KC	0.3069	0.3091	1.0000					
(4) SOC	0.3135	0.3300	0.5654	1.0000				
(5) GEO	-0.0354	-0.0576	0.0216	0.0586	1.0000			
(6) INST	0.0022	-0.0236	-0.0229	-0.0407	0.0958	1.0000		
(7) EXPR	-0.0246	0.0212	-0.2379	-0.0842	-0.0518	-0.0898	1.0000	
(8) SIZE	0.1221	0.2146	0.0655	0.1065	-0.1510	-0.3636	0.3065	1.0000

Appendix 2: Robustness check results

[2.1] Negative binomial model, fixed-effects, categorical COG variables (COG_alt)

	(1)	(2)	(3)	(4)
COG_alt		.1611	.5214***	.4771***
		(.1086)	(.1055)	(.1053)
COG_alt^2		.0165	-.0786***	-.0707***
		(.0191)	(.0189)	(.0188)
COG_alt *KC		.582***	.5127***	.5062***
		(.1636)	(.1469)	(.1459)
COG_alt ^2 * KC		-.0919***	-.0746***	-.0728***
		(.0261)	(.0236)	(.0235)
KC		-.9896***	-1.0196***	-1.0179***
		(.2454)	(.2187)	(.2173)
SOC	-.1193***		.0709**	.0952***
	(.0241)		(.0307)	(.0309)
GEO	-1.2473***			-1.2826***
	(.1633)			(.1685)
INST	-.3753**			-.4405**
	(.1741)			(.1809)
EXPR	-.4571***		-.4681***	-.4788***
	(.0082)		(.0084)	(.0086)
SIZE	.0195			-.0039
	(.0649)			(.068)
Const	3.7221***	-.2668*	2.3285***	3.3051***
	(.6053)	(.157)	(.1545)	(.6446)
Obs.	21,758	21,758	21,758	21,758
Net effect	*na*	.2524	.1426	.1375
Log likelihood	-8311.75	-10632.86	-8256.72	-8214.56

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

[2.2] Panel logit model, random effects, binary dependent variables

	(1)	(2)	(3)	(4)
COG		.2198***	.6397***	.6488***
		(.0395)	(.0448)	(.0445)
COG ^2		-.1289***	-.3021***	-.2442***
		(.0244)	(.0272)	(.0273)
COG*KC		.1787***	.2097***	.2431***
		(.0387)	(.0409)	(.041)
COG ^2 * KC		-.0519***	-.0561***	-.0736***
		(.0188)	(.0201)	(.0203)
KC		-.7423***	-.571***	-.5807***
		(.0302)	(.0333)	(.0333)
SOC	-1.979***		-1.5719***	-1.5427***
	(.0631)		(.067)	(.0668)
GEO	.9449***			1.0356***
	(.204)			(.1991)
INST	.1682			.0967
	(.1768)			(.1725)
EXPR	-.9588***		-.7593***	-1.0297***
	(.0305)		(.0272)	(.0309)
SIZE	.9666***			.9578***
	(.0445)			(.0444)
Const	-1.5536***	-2.5378***	3.8113***	-1.106***
	(.3594)	(.0711)	(.2084)	(.3592)
Time dummies	yes	yes	yes	yes
Obs.	22,071	22,071	22,071	22,071
Net effect	*na*	.2196	.624	.6414
Log likelihood	-10065.52	-10981.46	-10107.74	-9810.80

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Abstract (Korean)

본 연구는 협력적 혁신의 맥락에서 인지적 근접성의 양면적 효과를 조사하고, 지식 복잡도의 조절 효과에 초점을 맞추었습니다. 미국 바이오 공학기술 분야의 USPTO 특허 데이터를 활용하여, 이 연구는 인지적 근접성이 협력적 혁신에 역 U 자형 효과를 가지는 것을 확인하였습니다. 더하여, 지식 복잡도가 증가함에 따라 최적의 인지적 근접성 수준도 증가하며, 복잡한 지식의 확산되기 어렵다는 특성으로 인해 발생함을 실증적으로 확인했습니다. 인지적 근접성의 한계효과 또한 지식 복잡도와 함께 증가했는데, 이는 복잡한 지식 분야는 전문적인 특성으로 인해 좁기 때문에, 작은 인지적 거리의 변화에도 민감하게 반응하기 때문입니다. 이는 인지적 근접성이 지식 흡수를 촉진하는 한편, 지식 그 자체의 복잡한 속성으로 인해 지식 확산과 학습이 방해된다는 의미입니다. 따라서 보다 복잡한 지식을 협력하고자 하는 조직은 인지적으로 가까운 파트너와 협력함으로써 최적의 협력 성과를 달성할 수 있습니다. 그러나, 조직이 최적의 인지적 거리를 달성하더라도, 낮은 복잡도 분야의 최적점보다 협력 성과는 낮게 나타납니다. 이러한 통찰은 조직의 협업 전략에 유용한 시사점을 제공하며, 정책 입안자와 이해관계자가 혁신 네트워크를 육성하고 지원 생태계를 조성하는 데 있어 지침을 제공합니다.

주요어 : 조직 간 협력 네트워크, 근접성 이론, 지식 복잡도, 지식 공간
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