Geographical Proximity and Manufacturing Innovation through Industry–Academia Collaboration

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Abstract

Formal R&D collaborations enable firms to leverage knowledge as a strategic resource for enhancing their competitive position in the market. However, the relationship between such collaboration and geographical proximity remains complex. To help explain mixed findings in existing research, we combine ideas from absorptive capacity and knowledge diversity preference. Our findings reveal an inverted U-shaped pattern between geographical proximity and industry–academia collaborative innovation. Weaker decay rate of absorption capacity intensifies this effect, whereas the pursuit of knowledge diversity mitigates it. Additionally, we identify that pro-innovation policies matter, and geographical features and industry competition degree serve as sources of heterogeneity. Furthermore, rather than expanding partnerships to other organizations, firms are more likely to retain benefits from existing collaborations to reduce competition within industry and strengthen their own market power. Collaboration with universities exhibits a stronger positive effect on firm survival, while working with top-tier universities tends to limit a firm's capacity for further innovation. This study offers a novel perspective for understanding the dynamics between geographical proximity and knowledge externalities, and provides practical insights for firms seeking to enhance competitiveness through industry–academia collaboration.

Keywords: *Geographical Proximity, Manufacturing Firm Innovation, Industry–Academia Collaboration, Patent Application*

JEL Classification: O36, R12, D21

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1 INTRODUCTION

In today's competitive landscape, knowledge serves as a critical driver of innovation and sustainable advantage for firms (Alcácer & Chung, 2007). This has led to increased attention on how firms can effectively identify and utilize externally generated knowledge. Firms generally obtain external knowledge through two main ways: pure knowledge spillovers, and formal R&D collaborations (Monjon & Waelbroeck, 2003). Knowledge spillovers occur when knowledge created by one organization inadvertently benefits others, often through mechanisms such as employee mobility, patent disclosures, or scientific publications (Fischer & Varga, 2003; Rosell & Agrawal, 2009). In contrast, many innovative firms choose formal collaborations specifically to access valuable knowledge resources (Bernal et al., 2022), which boosts the competitiveness of the partners (González-Piñero et al., 2021). These partnerships involve direct cooperation between organizations to exchange applied knowledge (Audertsch et al., 2025), which is an important factor influencing firms' pursuit of innovation (Enkel et al., 2009). Meanwhile, academic institutions stand out as fundamental sources of such knowledge, having historically played a pivotal role in nurturing high-technology clusters worldwide (Bresnahan & Gambardella, 2004).

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As knowledge—sometimes also referred to as tacit knowledge—can mostly be transferred via personal contacts (Fischer & Varga, 2003; Audretsch & Feldman, 2003), numerous studies document that geographical proximity will induce knowledge spillovers (e.g., Jaffe et al., 1993; Audretsch & Feldman, 1996; Qiu et al., 2017). However, evidence on the link between geographical proximity and formal collaboration remains mixed. On the one hand, formal R&D collaboration often aims to addresses specific industry needs and societal demand (Lanzolla & Suarez, 2012), helping firms reduce cognitive and product development costs. Additionally, it serves as a channel for transforming basic knowledge obtained from spillovers into marketable solutions (Audertsch et al., 2025). In this sense, geographical proximity could be expected to diminish formal R&D collaborations, similar to what it does for knowledge spillovers. In contrast, the importance of geographical proximity declines in formally organized collaborative networks, especially in science-based sectors (Ponds et al., 2009). The "buzz-and-pipeline" framework further challenges the primacy of geography by highlighting how successful firms strategically combine vibrant local connections with strategic international pipelines (Bathelt et al., 2004). This suggests that formal R&D collaboration can thrive even over long distances. Thus, a key question arises: is closer geographical proximity always better for formal R&D collaborations?

We integrate insights from absorptive capacity (Cohen & Levinthal, 1990) and preference for knowledge diversity to reconcile contradictory findings in the literature. While most related studies rely on patent citations (Jaffe et al., 1993; Singh & Marx, 2013; Bai et al., 2024), publication co-authorship (Polidoro Jr. et al., 2022), or survey data (Monjon & Waelbroeck, 2003; Fritsch & Franke, 2004) to measure the formal collaboration or informal knowledge spillovers, we focus specifically on industry–academia collaborative patent applications. This approach captures a tangible innovation output and reflects the transition from knowledge spillovers to commercialization. Our study provides both a theoretical discussion and empirical tests of competing perspectives, challenging the conventional view that formal R&D collaboration is predominantly localized and best exchanged in close proximity (Acs et al., 1992).

Meanwhile, through the flow of both tacit and explicit information, formal R&D collaboration can broaden firms' range of knowledge (Badillo & Moreno, 2016; Li & Bosworth, 2020). Exposure to knowledge spillovers and prior collaborative experience impact firms' decisions on whether to initiate or sustain partnerships. Consequently, firms' decisions to start or continue collaborating with partners is intimately linked to whether it is already acquiring access to valuable knowledge through existing channels (Bernal et al., 2022). This dynamic raises a further question: how does "learning by collaboration" with universities shape firms' future innovation strategies? What is the role of universities' research capacity on firms' long-term survival?

We examine this question by analyzing the effects of different rolling-window collaboration on firms' subsequent innovation strategies. Most prior studies have assessed geographical influence using a single administrative unit, such as a country, state, or city area (e.g., Fischer & Varga, 2003; Qiu et al., 2017), which is spatially constrained. To overcome this limitation, we calculate the distance between firm and university using their longitude and latitude coordinates. This method enables a more accurate and continuous measure of geographical proximity, unconstrained by regional or administrative boundaries.

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2 LITERATURE REVIEW

Studies examining the relationship between geographic proximity and knowledge spillovers are most intimately related to our analysis. Marshall (1920) suggests that inter-firm knowledge spillovers is one of the reasons that induces firm to agglomerate. Based on state-level patent data, Jaffe et al. (1993) provided early evidence of this connection by demonstrating that inventors prefer to cite others located nearby. Subsequent studies have consistently confirmed a strong positive relationship between proximity and knowledge spillovers, particularly for tacit knowledge (e.g., Adams & Jaffe, 1996; Fischer & Varga, 2003; Audretsch & Feldman, 1996). Many of these studies, however, have examined the phenomenon using only a single geographic unit—such as a country, state, or city area (Monjon & Waelbroeck, 2003; Fischer & Varga, 2003; Qiu et al., 2017). Koch and Simmler (2020) further conceptualize knowledge spillovers as a process in which third parties advance basic scientific knowledge, which then flows over to firms located nearby. In contrast, Singh and Marx (2013) indicate that both country and state borders independently influence knowledge diffusion, even after accounting for the effects of geographic proximity such as metropolitan collocation or shorter intra-regional distances. Greater knowledge spillovers from academics would enhance firm productivity, while geographic proximity to universities may amplify such effects (Correia & Petiz, 2007; Yasar & Paul, 2012).

Second, this study contributes to the literature on R&D collaboration. According to the knowledge-based view, firms engage in collaboration to access external knowledge, expertise, and capabilities not available internally (Chesbrough et al., 2006). Such collaboration helps firms obtain resources they lack and enables partners address costs and risks together (Hagedoorn, 1993; Antonioli et al., 2017). While collaboration plays a relatively limited role in facilitating knowledge spillovers (Fritsch & Franke, 2004), Audertsch et al. (2025) contend that firms strategically choose between collaboration and spillovers by weighing both cost efficiency and potential complementary benefits. Notably, highly innovative firms tend to benefit more from collaboration, especially with remote universities possessing frontier knowledge (Monjon & Waelbroeck, 2003). These partnerships enable firms not only to accelerate organizational learning but also to develop valuable breakthroughs, thereby enhancing their collaborative performance (Belitski et al., 2023).

Third, our research relates to work that challenges the assertion that geographical proximity alone generates meaningful benefits. Central to this critique is the concept of absorptive capacity (Cohen & Levinthal, 1990). Studies consistently show this capacity significantly influences how effectively organizations benefit from knowledge spillovers (Qiu et al., 2017; Bai et al., 2024). While geographic proximity facilitates collaboration through face-to-face interaction (Jeong et al., 2014), knowledge from international academic collaborations tends to be more advanced, requiring robust absorptive capacity for effective utilization (Qiu et al., 2017). Beyond geographic proximity, cognitive and social proximity are increasingly recognized as playing a dominant role in facilitating knowledge flows, particularly over longer distances (Hu et al., 2024). The geographical scope of knowledge flows has been further clarified by the "buzz-and-pipeline" framework, which emphasizes maintaining both domestic and international knowledge connections (Bathelt et al., 2004). This perspective has been widely supported in subsequent research (Trippl et al., 2018; Breschi & Lenzi, 2016; Turkina & Van Assche, 2018), highlighting how distant knowledge linkages provide access to diverse knowledge pools that enhance local innovation. Recently, Cao et al. (2024) have highlighted that the growth of such connections and urban innovation in the past decade has been significantly enabled by improvements in transportation, logistics, and intercity connectivity.

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3 THEORY

We develop a theoretical model to analyze the impact of geographical proximity on industry–academia collaboration. First, we describe firm's R&D investment decisions to maximize its expected profits. Second, we discuss how geographical distance influences collaborative innovation through absorptive capacity and knowledge diversity.

3.1 Firm's collaborative innovation decision

We start with the analysis of the profit from collaborative innovations. Suppose firm i decides to engage in collaborative innovation with university j, aiming to maximize its profit by choosing the optimal R&D investment. The firm's initial profit is π_{0i}. If the collaboration is successful, the profit at the end of the period will increase by γ_{ij}, so that $\pi_{1i} = \left(1+\gamma_{ij}\right)\pi_{0i}$, where $\gamma_{ij} > 0$. If the collaboration fails, the profit remains stable, implying $\pi_{1i} = \pi_{0i}$. Owing to the uncertainties in innovative activities, the expected profit from collaborative innovations is influenced by the success rate μ_{ij}, and we have

$$E\left(\Delta\pi_{1,ij}\right) = \left(1-\mu_{ij}\right)\pi_{0i} + \mu_{ij}\left(1+\gamma_{ij}\right)\pi_{0i} - \pi_{0i} = \mu_{ij}\gamma_{ij}\pi_{0i} \tag{1}$$

Accounting for the cost and uncertainty of innovative activities, along with the insights from Aghion and Howitt (2009), we model the success rate μ_{ij} of collaborative innovation as a positive function of its innovative inputs R_{ij}, that is, $\mu_{ij} = \phi(R_{ij})$. We assume the firm's innovation function takes a Cobb-Douglas form, that is, $\mu_{ij} = \lambda_{ij}R_{ij}^{\sigma}$, where λ_{ij} represents the efficiency of collaborative innovative activities, and the elasticity $\sigma \in (0,1)$. Therefore, greater investment in collaborative innovative activities increases the likelihood of achieving successful innovation.

The collaboration requires an ex-ante investment of R_{ij}, which constitutes a sunk R&D cost. Therefore, the firm chooses innovative inputs to maximize its expected net profit, which is

$$E\left(\Pi_{1,ij}\right) = \mu_{ij}\gamma_{ij}\pi_{0i} - \tau_{ij}R_{ij} = \lambda_{ij}\gamma_{ij}\pi_{0i}R_{ij}^{\sigma} - R_{ij}. \tag{2}$$

The optimal input R_{ij} satisfies the "research arbitrage equation":

$$\sigma\lambda_{ij}\gamma_{ij}\pi_{0i}R_{ij}^{\sigma-1} = 1. \tag{3}$$

The firm's optimal investment and success rate of collaborative innovation are:

$$R_{ij}^{*} = \left(\sigma\lambda_{ij}\gamma_{ij}\pi_{0i}\right)^{\frac{1}{1-\sigma}}, \tag{4}$$

$$\mu_{ij}^{*} = \lambda_{ij}^{\frac{1}{1-\sigma}}\left(\sigma\gamma_{ij}\pi_{0i}\right)^{\frac{\sigma}{1-\sigma}}\ . \tag{5}$$

3.2 Geographical distance and collaborative innovation

Let D_{ij} denotes the distance between firm i and its collaborative university j, which is exogenously given and always greater than or equal to zero. According to Equations (4) and (5), both the optimal investment and success rate are related to the efficiency of collaborative innovative activities λ_{ij} and excess profit proportion created by collaborative innovation γ_{ij}. Furthermore, geographical distance influences these two factors.

First, geographical proximity facilitates knowledge spillovers (Adams & Jaffe, 1996), which are rarely isolated from absorptive capacity (Bai et al., 2024). As a firm's absorptive capacity relates to its technical capabilities (Alcácer & Chung, 2007), a higher λ_{ij} indicates stronger absorptive capacity, that is, λ_{ij} is positively correlated with absorptive capacity. As firms receiving distant knowledge usually have greater absorptive capacity (Qiu et al., 2017), we let $\lambda_{ij} = A(D_{ij}; \chi_i, \tau)$, where τ is a general parameter of absorptive capacity and χ_i is the decline rate of absorptive capacity with distance, which depends on firm heterogeneity. Assume that λ_{ij} decreases with geographical distance D_{ij}, but at a glowing rate. Thus, we have $\frac{\partial \lambda_{ij}}{\partial D_{ij}} < 0$ and $\frac{\partial^2 \lambda_{ij}}{\partial D_{ij}^2} > 0$.

Second, the "buzz-and-pipeline" theory suggests that long-distance collaborations afford firms access to more diverse knowledge sources (Bathelt et al., 2004). Therefore, we assume that knowledge diversity increases with distance. This relationship can be represented by the function $\gamma_{ij} = V(D_{ij}; \phi_i, \upsilon)$, where υ is a general parameter of absorptive capacity and ϕ_i is the elasticity of profit gains from innovation with respect to distance, which can be treated as an index of "the demand for knowledge diversity" and depends on firm heterogeneity. As access to more diverse knowledge is expected to bring greater profits, the additional profit ratio γ_{ij} increases with collaboration distance D_{ij}, but at a decreasing rate. This is expressed mathematically as $\frac{\partial \gamma_{ij}}{\partial D_{ij}} > 0$ and $\frac{\partial^2 \gamma_{ij}}{\partial D_{ij}^2} < 0$.

We focus on the effects of geographical distance on collaborative innovations here. As innovation output is positively related to innovation success rate, differentiating firm's optimal success rate μ_{ij}^* with respect to D_{ij} based on Equation (5) yields

$$\frac{\partial \mu_{ij}^*}{\partial D_{ij}} = \frac{\sigma}{1-\sigma} \frac{\mu_{ij}^*}{\gamma_{ij}} \frac{\partial \gamma_{ij}}{\partial D_{ij}} + \frac{1}{1-\sigma} \frac{\mu_{ij}^*}{\lambda_{ij}} \frac{\partial \lambda_{ij}}{\partial D_{ij}}. \tag{6}$$

According to Equation (6), geographical distance influences collaborative innovations through two channels: first, by increasing knowledge diversity, which enhances the profit gains from innovation; second, by reducing absorptive capacity, which suppresses collaborative R&D efficiency. For simplicity, let $\gamma_{ij} = V(D_{ij}; \phi_i, \upsilon) = \upsilon D_{ij}^{\phi_i}$, where $\upsilon > 0$ and $0 < \phi_i < 1$, and let $\lambda_{ij} = A(D_{ij}; \chi_i, \tau) = \tau e^{-\chi_i D_{ij}}$, where $\tau > 0$ and $\chi_i > 0$[1]. Equation (5) can be rewritten as

$$\mu_{ij}^* = (\tau e^{-\chi_i D_{ij}})^{\frac{1}{1-\sigma}} (\sigma \pi_{0i} \upsilon D_{ij}^{\phi_i})^{\frac{\sigma}{1-\sigma}} = M D_{ij}^{\frac{\sigma \phi_i}{1-\sigma}} e^{-\frac{\chi_i}{1-\sigma} D_{ij}}, \tag{7}$$

where $M = \tau^{\frac{1}{1-\sigma}} (\sigma \upsilon \pi_{0i})^{\frac{\sigma}{1-\sigma}}$. Moreover, Equation (6) can be expressed as

$$\frac{\partial \mu_{ij}^*}{\partial D_{ij}} = \frac{\mu_{ij}^*}{(1-\sigma) D_{ij}} (\sigma \phi_i - \chi_i D_{ij}). \tag{8}$$

[1] We adopt these specific functional forms mainly to keep the analysis tractable and to focus on the key relationship between geographical distance and industry–academia collaborative innovation through absorptive capacity and knowledge diversity. However, we recognize that knowledge spillovers in practice may involve non-linear effects, and the role of geographical distance is likely more complex than our simplified measure captures. Further research could extend our study by incorporating more flexible functional forms or employing actual flow data to address the robustness of this study under more complex assumptions.

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First, we address how firm heterogeneity on absorptive capacity moderates the impact of geographical distance on collaborative innovation. This firm heterogeneity includes factors such as industry characteristics and competitive environment. For example, technology-intensive firms or firms experiencing high competition have higher absorptive capacity, which implies that their decline rate of absorptive capacity χ_i is smaller. Differentiating Equation (8) with respect to χ_i, we have

$$\frac{\partial^2 \mu_{ij}^*}{\partial D_{ij} \partial \chi_i} = -\frac{\mu_{ij}^*}{1-\sigma}\left[1 + \frac{\chi_i\left(D_{ij}^* - D_{ij}\right)}{1-\sigma}\right] \tag{9}$$

According to Equation (9), the conditions $\frac{\partial^2 \mu_{ij}^*}{\partial D_{ij} \partial \chi_i} < 0$ is always satisfied when $D_{ij} \leq D_{ij}^*$. When $D_{ij} > D_{ij}^*$, the condition is highly likely to be satisfied if $\chi_i/(1-\sigma)$ is sufficiently small. Consequently, $\frac{\partial^2 \mu_{ij}^*}{\partial D_{ij} \partial \chi_i} < 0$ generally holds. Thus, we have the following prediction:

Lemma 1 *A firm with higher absorptive capacity will experience a smaller impact of geographical distance on its collaborative innovation outputs.*

Second, we discuss how the geographical distance of industry–academia collaboration affects collaborative innovations. According to Equation (8), the optimal distance $D_{ij}^* = \frac{\sigma \phi_i}{\chi_i}$, which satisfies $\frac{\partial \mu_{ij}^*}{\partial D_{ij}} \begin{cases} > 0, & if\ \ D_{ij} < D_{ij}^* \\ = 0, & if\ \ D_{ij} = D_{ij}^* \\ < 0, & if\ \ D_{ij} > D_{ij}^* \end{cases}$. We, therefore, have the following conclusion:

Lemma 2 *The geographical distance of industry–academia collaboration has an inverted U-shaped relationship with their collaborative innovations.*

Third, we examine the role of firm heterogeneity on knowledge diversity demand in such effects. This kind of firm heterogeneity includes knowledge sources and types. Suppose the following case: firms A and B have the same absorptive capacity ($\chi_A = \chi_B = \chi$) but different demand of knowledge diversity ($\phi_A > \phi_B$), then Firm A will have a larger optimal distance for collaborative innovation outputs than Firm B because

$$D_{Aj}^* - D_{Bj}^* = \frac{\sigma}{\chi}(\phi_A - \phi_B) > 0 \tag{10}$$

Thus, we have the following prediction:

Lemma 3 *A firm with greater demand for knowledge diversity will have a larger optimal geographical distance for collaborative innovation outputs.*

As geographical proximity is inversely related to geographical distance, for simplicity, we define geographical proximity as the inverse function of distance, that is, $P_{ij} = D_{ij}^{-1}$ and $P_{ij}^* = \frac{\chi_i}{\sigma \phi_i}$, which satisfies $\frac{\partial \mu_{ij}^*}{\partial P_{ij}} \begin{cases} > 0, & if\ \ P_{ij} < P_{ij}^* \\ = 0, & if\ \ P_{ij} = P_{ij}^* \\ < 0, & if\ \ P_{ij} > P_{ij}^* \end{cases}$. Combining with the conclusions above, we have following propositions:

Proposition 1 *A firm with higher absorptive capacity will experience a greater impact of geographical proximity on its collaborative innovation outputs.*

Proposition 2 *The geographical proximity of industry–academia collaboration has an inverted U-shaped relationship with their collaborative innovations.*

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Proposition 3 *A firm with greater demand for knowledge diversity will have a lower optimal geographical proximity for collaborative innovation outputs.*

4 DATA AND EMPIRICAL METHODOLOGY

4.1 Data

Our study integrates data from triple sources. We measure innovation output using patent data from China's State Intellectual Property Office (SIPO), containing comprehensive records of all patent applications filed since 1985. The dataset includes detailed information such as applicant names, patent titles, application dates, and patent type. While utility models and designs typically reflect incremental modifications, invention patents represent substantial technological advances with significant impacts on products and processes. Here we focus specifically on invention patents that were jointly filed by firms and universities as our measure of collaborative innovation output[2].

The second dataset we utilized is from China's State Administration for Industry and Commerce (SAIC), which includes administrative information pertaining to all firms in China since 1949, including those that have been deregistered or revoked. It provides firm details including name, address, registration date, ownership, industry category, etc. We collect the information of all manufacturing firms located in Fujian province and link them with the SIPO dataset by the names of applicants[3].

The geographical coordinates (longitude and latitude) of both firms engaged in collaborative innovation and their partner universities are obtained using the *Amap* (Gaode) Maps Application Programming Interface (API). This platform provides a suite of tools to integrate mapping, location searching, routing, and other geographical services into the applications. The pairwise distances, in kilometer, between each firm and university are calculated based on these coordinates.

Other city-level data derives from the CEIC database, which provides comprehensive indices on the economic and social development of Chinese cities. Thus, we build a database covering 217,802 Chinese manufacturing firms and linking innovation and geographical distance data from 2000 to 2020, which contains 1,812,513 observations.

4.2 Empirical strategy

Based on the findings in the existing literature and the predictions from the theoretical model, we first conduct an Ordinary Least Squares (OLS) regression to explore the effects of geographical proximity on industry－academia collaborative innovation:

$$Y_{cit} = \beta_1 Proximity_{cit} + \boldsymbol{X}'_{c,t-1}\boldsymbol{\Gamma} + z_i + \omega_t + \varepsilon_{cit}. \tag{11}$$

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2 The *Patent Law of the People's Republic of China* remarks that "Invention means any new technical solution proposed for a product, a process or the improvement thereof"; "Utility model means any new technical solution proposed for the shape, the structure, or their combination, of a product, which is fit for practical use. Design means, with respect to an overall or partial product, any new design of the shape, the pattern, or their combination, or the combination of the color with shape or pattern, which is rich in an aesthetic appeal and is fit for industrial application."

3 We choose Fujian as the research sample for the following reasons: first, Fujian's GDP ranks among the top in China, while avoiding the potential sample selection bias that might arise from choosing first-tier cities such as Beijing, Shanghai, Guangzhou, or Shenzhen; second, there is significant regional economic disparity within the province, with considerable differences between coastal and inland areas, making it suitable for examining how spatial structure and geographical factors lead to heterogeneity. Therefore, selecting Fujian as the research sample offers strong representativeness.

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In order to test the inverted U-shaped pattern, we introduce a quadratic term of $Proximity_{cit}$ in the regression:

$$Y_{cit} = \beta_1 Proximity_{cit} + \beta_2 Proximity_{cit}^2 + \boldsymbol{X}'_{c,t-1}\boldsymbol{\Gamma} + z_i + \omega_t + \varepsilon_{cit}. \quad (12)$$

Here, Y_{cit} is invention patent applications jointly applied by firm and university to measure the collaborative innovation outputs for firm *i* in year *t*; *c* represents city. $Proximity_{cit}$ denotes the geographical proximity of industry – academia collaboration, which is defined as the inverse of average distance between firm and each university it collaborated with in that year[4]. We include a city-level vector of controls $\boldsymbol{X}_{ct}$, which contain the population (*Population*); GDP per capital (*GDP_pc*); the proportion of researchers in colleges and universities (*Reseacher*); local public budget expenditure (*Pub_exp*); government supports for science and technology (*Tech_support*), that is, public budget ratio for science and technology; and transportation infrastructure (*Transport*), that is, road mileage per unit area. Except for *Teachers* and *Tech_support*, other control variables are in logarithm. ε_{cit} is an error term. We also include firm fixed effect z_i and year fixed effect ω_t. Table 1 presents the summary statistics. The coefficients of interest in this study are β_1 (which corresponds to χ_i in the model) and β_2 in order to identify the inflection point, which represents the optimal distance.

Tab. 1 – Summary statistics. Source: own research

Variables	Obs.	Min.	Max.	Mean	Std. Err.
Y	1,822,513	0	21	0.0005	0.0457
Proximity	1,822,513	0	2.1748	0.0000	0.0032
Population	1,566,258	7.6256	9.0780	8.5749	0.4633
GDP_pc	1,566,258	-4.9233	-2.1415	-2.9522	0.6363
Researcher	1,566,258	0.0001	0.0026	0.0011	0.0008
Pub_expe	1,499,790	7.3453	11.4614	10.2760	0.8926
Tech_support	1,499,790	0.0027	0.0421	0.0191	0.0091
Transport	1,604,069	0.2642	1.6104	1.0779	0.3647

Notes: (1) *Population*, *GDP_pc*, *Pub_expe* and *Transport* are in logarithm. (2) The original unit of population is thousand persons, the original unit of GDP per capita is billion yuan/thousand persons, and the original unit of local public budget expenditure is billion yuan.

5 EMPIRICAL FINDINGS

5.1 Baseline results

First, we examine the linear effects of geographical proximity on industry–academia collaborative innovation. Table 2 presents the estimation results from Equation (11). Results in columns (1) and (2) show that the geographical proximity affects industry–academia collaborative innovation positively. Regarding magnitude, geographical proximity on average increases firms' collaborative invention patent applications by 2.85 to 3.59. These results

[4] Even when collaborating with the same university, the research team involved is typically different. We, therefore, assume that a firm's all collaborations are independent and calculate the firm-university distance separately for each collaboration. As Bai et al. (2024) suggest, reduced travel time (such as introducing new airline routes) facilitates knowledge spillovers. However, for a given way of transportation, travel time between two locations is positively correlated with geographical distance. Therefore, using travel time as a measure of geographical proximity would only affect the magnitude of the estimated coefficients, but not the validity of the conclusions. Moreover, as all firms in our sample operate under the same national policies in China, unaccounted factors such as institutional or cultural differences are unlikely to substantially influence our results in the context of this study. Hence, the results obtained using the geographical proximity based on latitude and longitude do not compromise the validity of the conclusions.

confirm the pattern that collaborations are generally localized and decrease with geographical distance (e.g., Jaffe et al., 1993).

Tab. 2 – Baseline results. Source: own research

	Dependent variable: *# collaborative invention patents*				
	(1)	(2)	(3)	(4)	(5)
	Whole sample		Labor intensive	Capital intensive	Technology intensive
Proximity	2.8521*	3.5900**	8.0946***	5.4910***	2.3593*
	(1.4870)	(1.5304)	(1.8954)	(1.7777)	(1.3064)
Population		0.0043*	0.0030	-0.0053	0.0190
		(0.0022)	(0.0020)	(0.0040)	(0.0139)
GDP_pc		0.0020	0.0022	-0.0038*	0.0099
		(0.0013)	(0.0015)	(0.0021)	(0.0071)
Researcher		-0.4484	0.1544	-0.8110	-3.7005
		(0.4864)	(0.3712)	(0.7224)	(2.6031)
Pub_expe		0.0011*	-0.0007	0.0018	0.0062
		(0.0006)	(0.0005)	(0.0013)	(0.0042)
Tech_support		-0.0061	-0.0109	0.0294	-0.0700
		(0.0135)	(0.0100)	(0.0321)	(0.0869)
Transport		-0.0024***	-0.0015**	-0.0035*	-0.0047
		(0.0007)	(0.0007)	(0.0019)	(0.0035)
Constant	0.0005***	-0.0388**	-0.0108	0.0215	-0.1829
	(0.0000)	(0.0180)	(0.0130)	(0.0383)	(0.1151)
Year FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Observations	1822513	1469843	950956	326272	127376
R^2	0.2710	0.2819	0.2996	0.3205	0.2800

Notes: (1) Standard errors are reported in parentheses and clustered at firm level. (2) ***, **, and * represent significance at the 1%, 5% and 10% level, respectively. Same for following tables.

Based on our model's prediction, higher absorptive capacity reflects a slower decline rate as geographical distance increases, which in turn leads to a smaller β_1. Technologically leading firms usually have higher absorptive capacity, and are more likely to benefits from potential knowledge spillovers over long distance (Alcácer & Chung, 2007). Therefore, the absorptive capacity of firm belongs to labor-intensive industries declines at a faster rate as geographical distance increases compared to firm belongs to technology-intensive industries, that is, $\chi_i^{labor} > \chi_i^{technology}$, which implies $\beta_1^{labor} > \beta_1^{technology}$ in our empirical results. To test this prediction, we divide the whole sample by firm's sector: labor-intensive industry, capital-intensive industry, and technology-intensive industry[5]. Estimated results are reported in columns (3)–(5) of Table 2. For firms in labor-intensive industries, regarding magnitude, geographical proximity on average increases collaborative invention patent applications by 8.09, which is significantly greater than the corresponding effects on technology-intensive industries (2.36). These results align with **Proposition 1**.

[5] Based on the Industrial Classification for National Economic Activities of China (GB/T 4745-2017), this study categorizes the following 15 industries as labor-intensive industries: C13 – C24, C29, C41, and C42; the following eight industries as capital-intensive industries: C25, C30 – C35, C40; and the following eight industries as technology-intensive industries: C26 – C28, C36 – C39, and C43.

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Tab. 3 – Baseline results (with quadratic term). Source: own research

	Dependent variable: # collaborative invention patents				
	(1)	(2)	(3)	(4)	(5)
	Whole sample		Foreign firms	Domestic firms	With interaction
Proximity	11.6378***	11.2650***	10.1108***	13.3724***	3.4692**
	(2.0849)	(1.8559)	(2.1282)	(2.9173)	(1.7181)
Proximity^2	-5.4380***	-5.4271***	-9.7055***	-6.3778***	
	(1.0030)	(1.0116)	(2.5988)	(1.3804)	
*Proximity*d_F*					0.8307
					(2.0389)
Population		0.0024	-0.0013	0.0029	0.0042*
		(0.0020)	(0.0051)	(0.0023)	(0.0022)
GDP_pc		0.0011	-0.0003	0.0014	0.0020
		(0.0012)	(0.0036)	(0.0013)	(0.0013)
Researcher		-0.8751*	0.2447	-1.1131**	-0.4587
		(0.4547)	(0.7510)	(0.5131)	(0.4785)
Pub_expe		0.0011*	0.0007	0.0012*	0.0011*
		(0.0006)	(0.0015)	(0.0007)	(0.0006)
Tech_support		-0.0056	-0.0276	-0.0041	-0.0061
		(0.0131)	(0.0488)	(0.0136)	(0.0135)
Transport		-0.0021***	-0.0034	-0.0020***	-0.0024***
		(0.0007)	(0.0026)	(0.0007)	(0.0007)
Constant	0.0004***	-0.0254	0.0086	-0.0290	-0.0381**
	(0.0000)	(0.0164)	(0.0412)	(0.0182)	(0.0179)
Year FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Observations	1822513	1469843	144298	1324624	1469843
R^2	0.2381	0.3299	0.2816	0.3435	0.2821
Optimal distance	0.935	0.963	1.920	0.954	--

The results with quadratic term of geographical proximity are shown in Table 3. We identify significantly negative coefficient of *Proximity*^{2}, which reveals the inverted U-shaped pattern between geographical proximity and collaboration innovations. These results are in line with **Proposition 2**. The average optimal distance of collaboration is 0.935km to 0.963km. To isolate the effects of knowledge diversity from the overall effects, we classify foreign-funded firms and domestic firms into two sub-samples. First, we introduce an additional regressor *Proximity*D_F* in Equation (11) where *D_F* is a dummy variable for foreign-funded firms. There are no significant differences of absorptive capacity between foreign-funded firms and domestic firms (column (5) in Table 3). Therefore, we assume that $\chi_i^{foreign} = \chi_i^{domestic}$. Moreover, as distant knowledge linkage enables firms to tap into diversified pools of knowledge (Turkina et al., 2025), and foreign-funded firms can utilize the technology of their parent firms, these firms usually have more diverse knowledge than domestic firms. Thus, we have $\phi_i^{foreign} > \phi_i^{domestic}$. Combining with the condition $D_{ij}^* = \frac{\sigma\phi_i}{\chi_i}$, we have $D_{foreign}^* > D_{domestic}^*$. Columns (3) and (4) of Table 3 suggest that the optimal distance of foreign-funded firms is approximately two-times as the optimal distance of domestic firms, which is consistent with this prediction. These results confirm the pattern shown in **Proposition 3**, that is, the demand of firms for knowledge diversity can partially offset the negative effects induced by the increase in geographical distance.

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5.2 Robustness checks

We conduct robustness checks on the baseline results examined in Section 5.1. First, to alleviate the concern that our results might be affected by the fact that most firms have never applied invention patents or never collaborated with other organizations, we restrict our sample based on firms' innovation experiences. Second, we further address the potential measurement bias by using alternative measures of geographical proximity and collaborative innovation outputs. Finally, we apply the Poisson Pseudo-Maximum Likelihood method to eliminate potential estimation bias.

5.2.1 Sub-sample analysis based on firm's innovation experience

Our baseline analysis includes firms that have never applied invention patents or do not have collaboration experiences, which may induce potential selection bias. To alleviate such concern, we exclude such firms from our sample period. Table A1 in the Appendix presents the regression results. The coefficients of *Proximity* are close to our baseline results (Table 2) and still positive and statistically significant. These results reaffirm the inverted U-shaped links between geographical proximity and collaborative outputs, confirming our findings are not driven by this potential sample selection bias.

5.2.2 Alternative measure of geographical proximity

In the aforementioned analysis, geographical proximity is calculated as the inverse of the average distance between a firm and each of its partner universities. However, this measure experiences potential measurement bias for two reasons. First, it only considers collaborations from the current year, ignoring the cumulative experience from past collaborations. Second, it does not account for the quantity of innovation output, such as when an invention patent results from a collaboration with multiple universities. To address this concern, we introduce two alternative measures. The former is defined as the inverse of the average distance on all university collaborations up to the current year, denoted as *Proximity_all*. The latter is the inverse of per-patent average distance, calculated by dividing the cumulative distance of all collaborations by the total invention patent count, denoted as *Proximity_perpatent*. Estimated results are reported in Table A2 in the Appendix. The results remain statistically indistinguishable from our baseline results, providing additional support of our main conclusions.

5.2.3 Alternative measure of collaborative innovation output

Our baseline regression examines the relationship between geographical proximity in a given year and new collaborative invention patents, without accounting for the stock of past collaborations. This measure could induce potential measurement bias because it fails to capture the dynamic nature of the collaboration process, as a firm's current innovation output is likely built upon the accumulated knowledge and experience from its entire history of partnerships. Thus, we re-estimate the model applying the cumulative invention patent count as the dependent variable to test whether the inverted U-shaped pattern holds for the stock of outcomes generated by firms' enduring relationships. The estimates presented in Table A3 confirms that our findings are not driven by this potential measurement bias.

5.2.4 Using PPML method to estimate the effects

As we apply invention patents as the dependent variable, which is a non-negative integer variable with a significant fraction of zeros, the application of OLS to such data can yield inconsistent estimates. We, therefore, employ a Poisson Pseudo-Maximum Likelihood estimator, which is robust to both discrete nature of data and high incidence of zero values. Although the PPML estimates are substantially larger in magnitude and the sample size is

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reduced, the inverted U-shaped relationship remains statistically significant (Table A4). This again provides strong evidence for the robustness of our primary results.

5.2.5 Excluding firms located in districts that have newly established university towns

As knowledge can serve as a source of competitive advantage, firms may adjust their location strategies to pursue external knowledge through knowledge spillovers (Alcácer & Chung, 2007). This may, in turn, lead to reversed causality, that is, firms may locate universities nearby to facilitate knowledge spillover, thereby increasing collaboration. To address this concern, we exclude firms located in districts or counties where new university towns were established during the sample period[6] and re-estimate the effects of geographic proximity. The results indicate that neither the linear term nor the quadratic term coefficients change significantly (see Table A5). This further provides robust evidence and helps mitigate the endogeneity concern.

5.3 Heterogeneous effects

This section investigates the heterogeneity in the effects of geographical proximity across different time periods and geographical locations. First, we empirically examine how these effects are shaped by the implementation of innovation stimulation policies; second, how they vary between coastal and inland cities; and third, what is the role of industry competition degree.

5.3.1 Role of pro-innovation national policies in China

Tab. 4 – Heterogeneous effect: role of pro-innovation policies in China. Source: own research

	Dependent variable: *# collaborative invention patents*			
	(1)	(2)	(3)	(4)
	Before 2006	During and after 2006	2006-2014	During and after 2015
Proximity	0.4853***	6.4319***	10.8359***	6.4946***
	(0.0300)	(1.5991)	(2.9666)	(1.6701)
Population	-0.0113	0.0033	0.0013	0.0135
	(0.0137)	(0.0029)	(0.0037)	(0.0132)
GDP_pc	0.0020	0.0016	0.0000	0.0033
	(0.0025)	(0.0019)	(0.0017)	(0.0042)
Researcher	0.9847	-0.8099	-1.1497*	-0.3701
	(1.1890)	(0.6170)	(0.5976)	(4.1249)
Pub_expe	0.0029	0.0012	0.0001	0.0034
	(0.0061)	(0.0008)	(0.0006)	(0.0024)
Tech_support	0.3683	-0.0049	0.0196	-0.0328*
	(0.3656)	(0.0135)	(0.0173)	(0.0194)
Transport	-0.0018	-0.0020**	-0.0005	-0.0000
	(0.0058)	(0.0009)	(0.0008)	(0.0051)
Constant	0.0776	-0.0320	-0.0109	-0.1434
	(0.1273)	(0.0202)	(0.0274)	(0.1175)
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Observations	76436	1385364	610666	763383
R^2	0.5193	0.3102	0.3836	0.3751

During our sample period, China's central government initiated pro-innovation policies to encourage firms or universities to innovate. A key starting point was in 2006, when the national innovation campaign was launched. As a part of this, the State Council released the *National Medium- to Long-Term Plan for the Development of Science and Technology (2006–2020)*,

[6] Four districts constructed new university towns during our sample period: the Cangshan District and Minhou County in Fuzhou, and the Jimei and Xiang'an Districts in Xiamen.

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aiming to promote innovation capabilities of Chinese firms, and building an innovative society by 2020. To support this, the government increased subsidies and grants and enhanced resource availability for firms. Meanwhile, since 2006, China has continuously adjusted ownership of intellectual property post-commercialization. Notably, aiming to motivate universities to innovate and improve the commercialization rate of innovations, the *Law on Promoting the Transformation of Scientific and Technological Achievements* was implemented in 2015, which represents a significant shift by transferring the rights of use, disposition, and revenue from the state directly to universities. This policy is often characterized as "China's Bayh-Dole Act," which granted universities extensive rights to patent and retain ownership of innovations produced with government-funded projects.

Such pro-innovation policies created a stronger incentive for firms and universities to engage in collaborative innovations. Referring to Huang et al. (2024), we divide our sample into periods before and after 2006, from 2006 to 2014, and after 2015 to ascertain changes in the role of geographical proximity. As Table 4 shows, before 2006, closer geographical proximity was associated with an average increase of 0.49 collaborative invention patent applications. After 2006, its impact surged to 6.43, and reached 10.84 during 2006–2014. This evidence strongly suggests that pro-innovation policies amplified the impact of geographical proximity on collaborative innovations.

5.3.2 Geographical features: coastal and inland cities

Tab. 5 – Heterogeneous effect: coastal and inland cities. Source: own research

	Dependent variable: *# collaborative invention patents*				
	(1)	(2)	(3)	(4)	(5)
	Inland cities		Coastal cities		With interaction
Proximity	4.3872***	35.8503***	3.4634**	12.0602***	3.4633**
	(1.2776)	(10.4621)	(1.6944)	(2.3896)	(1.6944)
Proximity ^{2}		-38.5370***		-5.6965***	
		(12.4130)		(1.1323)	
*Proximity*d_I*					0.9242
					(2.1223)
Population	0.0011	-0.0005	0.0080***	0.0052**	0.0044*
	(0.0180)	(0.0163)	(0.0026)	(0.0022)	(0.0022)
GDP_pc	0.0024	0.0005	0.0035**	0.0022*	0.0020
	(0.0028)	(0.0022)	(0.0014)	(0.0013)	(0.0013)
Researcher	0.5585	-0.1548	-0.2832	-0.7668	-0.4532
	(3.4316)	(3.2053)	(0.5207)	(0.4863)	(0.4823)
Pub_expe	0.0008	0.0010	0.0011*	0.0012*	0.0011*
	(0.0037)	(0.0037)	(0.0007)	(0.0006)	(0.0006)
Tech_support	-0.0471	-0.0517	-0.0042	-0.0042	-0.0059
	(0.0554)	(0.0542)	(0.0131)	(0.0126)	(0.0135)
Transport	0.0035	0.0042	-0.0002	-0.0004	-0.0023***
	(0.0034)	(0.0034)	(0.0007)	(0.0006)	(0.0007)
Constant	-0.0093	-0.0053	-0.0694***	-0.0490***	-0.0391**
	(0.1278)	(0.1147)	(0.0205)	(0.0175)	(0.0180)
Year FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Observations	171211	171211	1298632	1298632	1469843
R^2	0.1933	0.2872	0.2935	0.3472	0.2822
Optimal distance	--	2.150	--	0.945	--

There exists a global trend of population and economic activity being highly concentrated in coastal areas; it is also true for China. Although the GDP per capita gap between coastal and inland areas has narrowed globally in recent years, coastal regions continue to maintain an

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economic lead because of their geographical advantages (Jin et al., 2024). Compared to coastal areas, inland regions often experience challenges in infrastructure connectivity, with lags in development and lower levels of population agglomeration (Su et al., 2025). This spatial imbalance provides a fundamental context for understanding the coastal–inland divide in China.

We argue that such imbalance may create a "knowledge diversity gap." Coastal firms enjoy the advantages of agglomeration economies. They are usually surrounded by abundant local universities and superior transportation networks, which facilitates capturing localized knowledge spillovers through frequent personal interactions. In contrast, firms in inland cities typically experience less developed and less diverse knowledge, forcing them to seek more advanced and diverse knowledge from geographically distant sources. Therefore, we hypothesize that the demand for knowledge diversity is inversely related to regional development, that is, it is higher in inland cities.

Our split-sample analysis confirms this structural difference (Table 5). First, the interaction term has insignificant coefficient in column (5), suggesting that firms' absorptive capacity does not differ significantly between coastal cities and inland cities, that is, $\chi_i^{inland} = \chi_i^{coastal}$. Second, more importantly, the optimal collaboration distance calculated from the regression is substantially larger for inland cities (columns (2) and (4)). So, we have $D^*_{inland} > D^*_{coastal}$. Combining with the condition $D^*_{ij} = \frac{\sigma\phi_i}{\chi_i}$, then we have $\phi_i^{inland} > \phi_i^{coastal}$. These findings support our hypothesis, that is, inland firms need a wider geographical reach to access diverse knowledge owing to the geographical constraints.

5.3.3 Role of industry competition degree

Tab. 6 – Heterogeneous effect: role of industry competition degree. Source: own research

	Dependent variable: *# collaborative invention patents*					
	# firms in the industry			*Technology intensive*		
	(1)	(2)	(3)	(4)	(5)	(6)
	Low	High	With interaction	No	Yes	With interaction
Proximity	8.5506**	2.5087**	5.9175***	6.8737***	2.3593*	6.8734***
	(3.9663)	(1.2761)	(1.5333)	(1.4486)	(1.3064)	(1.4485)
*Proximity*d_H*			-3.1507*			
			(1.7208)			
*Proximity*d_tec*						-4.5138**
						(1.9508)
Population	0.0122*	0.0015	0.0041*	0.0017	0.0190	0.0038*
	(0.0069)	(0.0018)	(0.0022)	(0.0017)	(0.0139)	(0.0022)
GDP_pc	0.0050	0.0004	0.0019	0.0009	0.0099	0.0017
	(0.0036)	(0.0012)	(0.0013)	(0.0012)	(0.0071)	(0.0013)
Researcher	-0.4054	-0.0393	-0.5021	-0.1047	-3.7005	-0.6187
	(1.0737)	(0.3411)	(0.4723)	(0.3341)	(2.6031)	(0.4583)
Pub_expe	0.0017	0.0006	0.0011*	0.0002	0.0062	0.0011*
	(0.0023)	(0.0005)	(0.0006)	(0.0005)	(0.0042)	(0.0006)
Tech_support	-0.0465	0.0099	-0.0064	0.0012	-0.0700	-0.0045
	(0.0440)	(0.0125)	(0.0135)	(0.0111)	(0.0869)	(0.0134)
Transport	-0.0025	-0.0018**	-0.0024***	-0.0019***	-0.0047	-0.0021***
	(0.0017)	(0.0007)	(0.0007)	(0.0007)	(0.0035)	(0.0007)
Constant	-0.1016*	-0.0164	-0.0375**	-0.0112	-0.1829	-0.0350**
	(0.0568)	(0.0148)	(0.0176)	(0.0128)	(0.1151)	(0.0178)
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Observations	295704	1168003	1469843	1342467	127376	1469843
R^2	0.3440	0.3028	0.2895	0.3072	0.2800	0.2929

The degree of industry competition may lead to heterogeneity in this effect. Firms in highly competitive industries generally require greater competitiveness to survive. Consequently, they tend to develop stronger absorptive capacity. This capacity declines more slowly as the geographical distance in collaboration increases, that is, $\chi_i^{low-competition} > \chi_i^{high-competition}$, which implies that $\beta_1^{low-competition} > \beta_1^{high-competition}$ in our empirical results. To test this, we first split our sample based on whether the number of firms in an industry is above or below the annual median. Industries with more firms are classified as highly competitive, and those with fewer as less competitive. The results, shown in columns (1) – (3) of Table 6 indicate that for firms in less competitive industries, geographical proximity increases collaborative invention patents by an average of 8.55, which is significantly greater than in highly competitive industries.

Next, to account for industry characteristics, we divide our sample based on whether an industry is technology intensive. Compared to technology-intensive industries, others generally require a lower level of technology and have a slower pace of renewal and iteration. Consequently, competition is more intense in technology-intensive industries, which explains why firms in these industries possess stronger absorptive capacity. As discussed in Section 5.1, this implies $\chi_i^{non-tech\ intensive} > \chi_i^{tech\ intensive}$ and thus $\beta_1^{non-tech\ intensive} > \beta_1^{tech\ intensive}$. The results in column (4) – (6) of Table 6 confirm this pattern.

6 EXTENSION

6.1 Effect of collaboration on future innovation strategy

To reduce the costs for cognitive and product development, firms utilize the profits from learning and co-creation to engage in collaborations through which they can exchange applied knowledge between multiple directly engaged partners (Audretsch et al., 2025). Agazu and Kero (2024) conclude that numerous studies have identified a positive relationship and effect between innovation strategy and firm competitiveness. Therefore, firms can improve their competitiveness by enhancing innovation capabilities through industry–academia collaboration. Meanwhile, in addition to intellectual property protection, patents also enable firms to secure technological monopoly and establish market power. Under R&D budget constraints, firms can leverage the technical resource acquired through industry – academia collaboration to pursue further collaborative or independent innovation. Compared to independent innovation, these firms need to share resources, information, and technology with other institutions in subsequent collaborative innovation. Thus, if a firm subsequently chooses to pursue independent innovation, this can be viewed as retention of ownership of relevant technology from previous collaboration to enhance market power. If, however, the firm chooses to cooperate with other institutions after collaborating with a university, it is sharing what it learned. This would enhance the competitiveness of its partners, which may, in turn, intensify competition within the industry. This raises a few critical questions: What is the effect of "learning by collaboration"? Do such collaborations increase a firm's market power or encourage it to expand collaborations with other institutions?

To identify how "learning by collaboration" with universities influences a firm's future innovation strategy, we estimate the following OLS regression model:

$$Z_{cit} = \mu_1 d\_collaboration_{it}^n + \boldsymbol{X}'_{c,t-1}\boldsymbol{\Gamma} + z_i + \omega_t + \varepsilon_{cit}. \tag{13}$$

We introduce two dependent variables: the number of collaborative innovations with other institutions (excluding universities), and the number of independent innovations. $d\_collaboration_{it}^n$ is a dummy variable indicating for the existence of industry–academia collaborative innovation by firm i within n years prior to year t, where $n \in \{1,3,5\}$. Other controls are same as in Equation (11).

The results in Table 7 show that industry–academia collaboration does not increase firms' co-innovation with other institutions (columns (1)–(3)). Conversely, it significantly boosts firms' independent innovation output, and more recent collaborations have a greater impact than dated ones (columns (4)–(6)), with the coefficients dropping from 2.1690 to 0.0095. This implies that newer collaborative knowledge plays a more substantial role in enhancing firms' subsequent independent innovation. Furthermore, it indicates that through collaboration with universities, firms develop the capabilities for independent innovation. Rather than extending cooperation to other institutions, they are more likely to choose to keep these gains exclusive to avoid intra-industry competition and enhance their market power.

Tab. 7 – Extension: the effect of collaboration on future innovation strategy.
Source: own research

	Dependent variable					
	# other collaboration			*# independent innovation*		
	(1)	(2)	(3)	(4)	(5)	(6)
d_collaboration^1	1.2466			2.1690**		
	(0.9422)			(1.0373)		
d_collaboration^3		0.0048			0.0120***	
		(0.0037)			(0.0032)	
d_collaboration^5			0.0069			0.0095**
			(0.0042)			(0.0047)
Population	0.0334	0.0363	0.0374	0.1782***	0.1845***	0.1841***
	(0.0293)	(0.0307)	(0.0309)	(0.0415)	(0.0415)	(0.0416)
GDP_pc	0.0137	0.0156	0.0168	0.0027	0.0071	0.0071
	(0.0204)	(0.0205)	(0.0206)	(0.0247)	(0.0245)	(0.0250)
Researcher	-2.6073	-3.1699	-3.4198	-21.7380	-22.9358	-22.9563
	(7.0237)	(7.3627)	(7.4372)	(17.0151)	(17.0053)	(16.8591)
Pub_expe	-0.0133	-0.0130	-0.0133	0.0609***	0.0614***	0.0609***
	(0.0100)	(0.0101)	(0.0100)	(0.0233)	(0.0234)	(0.0235)
Tech_support	-0.0001	-0.0051	-0.0041	0.6230*	0.6092*	0.6182*
	(0.1830)	(0.1834)	(0.1832)	(0.3365)	(0.3369)	(0.3374)
Transport	-0.0161**	-0.0179**	-0.0188**	-0.0343	-0.0381*	-0.0385*
	(0.0077)	(0.0084)	(0.0088)	(0.0223)	(0.0227)	(0.0226)
Constant	-0.0853	-0.1058	-0.1083	-2.0578***	-2.1007***	-2.0935***
	(0.2660)	(0.2771)	(0.2765)	(0.4648)	(0.4670)	(0.4652)
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Observations	1469843	1469843	1469843	1469843	1469843	1469843
R^2	0.3293	0.3279	0.3279	0.4796	0.4790	0.4790

6.2 The role of research capacity of universities and a firm's long-term survival

The above analysis does not consider the research capacity of universities. Compared to ordinary universities (non-top-tier universities), top-tier universities hold advantages in research experience, personnel, and laboratory resources. If a firm collaborates with such universities, its collaborative innovation may have a twofold impact on its subsequent innovation. On the one hand, innovations resulting from cooperating with top-tier universities generally possess more advanced technology, enabling the firm to acquire more knowledge, which increases its subsequent innovations. On the other hand, collaborating with these universities often entails greater R&D investment and higher risks. This, in turn, leaves the firm with insufficient funds to support further innovation activities.

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To test this effect, we define universities listed under China's Project 211 and Project 985 as top-tier universities, with all others classified as ordinary universities[7]. We introduce a dummy variable d_top_i indicating whether a firm has collaboration with top-tier university, and then include its interaction term with $d\_collaboration_{it}^{n}$ in the regression. As shown in Table 8, cooperation with top-tier universities not only reduces firms' subsequent collaborative innovation with other institutions, but also diminishes their follow-up independent innovation. This indicates that collaborating with top-tier universities crowds out firms' R&D resources, rendering them unable to pursue other innovative activities. This raises a key question: which type of university collaboration is more conductive to s firm's long-term competitiveness?

Tab. 8 – Extension: the effect of collaboration with top-tier universities. Source: own research

	Dependent variable					
	# other collaboration			*# independent innovation*		
	(1)	(2)	(3)	(4)	(5)	(6)
d_collaboration^1	1.2172			2.0321**		
	(0.9471)			(1.0167)		
*d_collaboration^1*d_top*	-0.3313*			-1.5400***		
	(0.1795)			(0.4041)		
d_collaboration^3		0.0049			0.0121***	
		(0.0037)			(0.0032)	
*d_collaboration^3*d_top*		-0.4950*			-1.1765***	
		(0.2764)			(0.3696)	
d_collaboration^5			0.0070*			0.0097**
			(0.0042)			(0.0047)
*d_collaboration^5*d_top*			-0.7662*			-0.9253**
			(0.4334)			(0.4086)
Population	0.0330	0.0365	0.0372	0.1765***	0.1849***	0.1839***
	(0.0294)	(0.0307)	(0.0309)	(0.0412)	(0.0413)	(0.0415)
GDP_pc	0.0137	0.0161	0.0176	0.0027	0.0083	0.0080
	(0.0204)	(0.0205)	(0.0206)	(0.0247)	(0.0245)	(0.0250)
Researcher	-2.4145	-2.9521	-3.3095	-20.8418	-22.4181	-22.8231
	(7.0332)	(7.3479)	(7.4298)	(16.9977)	(16.9975)	(16.8586)
Pub_expe	-0.0131	-0.0128	-0.0133	0.0616***	0.0620***	0.0610***
	(0.0100)	(0.0101)	(0.0100)	(0.0232)	(0.0234)	(0.0235)
Tech_support	-0.0046	-0.0094	-0.0115	0.6022*	0.5991*	0.6093*
	(0.1832)	(0.1836)	(0.1834)	(0.3344)	(0.3363)	(0.3373)
Transport	-0.0146*	-0.0162*	-0.0174**	-0.0275	-0.0341	-0.0367
	(0.0079)	(0.0085)	(0.0089)	(0.0220)	(0.0226)	(0.0226)
Constant	0.2455	0.3849	0.6590	-0.5203	-0.9345*	-1.1670**
	(0.3566)	(0.4066)	(0.5344)	(0.5956)	(0.5441)	(0.5603)
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Observations	1469843	1469843	1469843	1469843	1469843	1469843
R^2	0.3295	0.3282	0.3284	0.4803	0.4792	0.4791

To achieve long-term survival and enhance prosperity, firms often engage in competitive battles using defined action repertoires (Smith et al., 2005). Meanwhile, firm survival usually serves as a critical measure of firm competitiveness. To further examine whether a firm's innovation experience contributes to firm survival, we identify if a firm exits the market within 1, 3, 5, and

[7] China's Project 211 and Project 985 were launched in 1995 and 1998, respectively. The former aims to build approximately 100 key universities and disciplines for national development; the latter focuses on cultivating world-class universities with global influence. These two projects have been integrated into the Double First-Class Initiative since 2019. The sample period being 2000 – 2020, we apply the list of these two projects as the basis for classification.

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10 years after current year based on the SAIC dataset, respectively, which is denoted as *d_exit*. A firm's innovation is categorized into two types: independent innovation and collaborative innovation. Collaborative innovation is further divided into three subtypes: cooperation with top-tier universities, cooperation with ordinary universities, and other collaborative innovation.

The results in Table 9 indicate that both university-collaborative innovation and independent innovation significantly reduce the probability of firm exit, while the effect of the former is approximately 10- to 30-times stronger than that of the latter. In contrast, collaboration with non-university institutions shows no significant impact on firm survival. Specifically, the effect of collaborative innovation with ordinary universities is approximately three-times greater than that with top-tier universities. This is likely due to the fact that cooperation with top-tier universities typically entails higher innovation costs and risks. Firms may be unable to absorb the sunk costs if their collaborative innovation fails, which diminishes its positive impact on the firm's long-term survival.

Tab. 9 – Extension: the effect of innovations on firm's long-term survival.
Source: own research

	Dependent variable: *d_exit*			
	(1)	(2)	(3)	(4)
	≤ 1 *year*	≤ 3 *years*	≤ 5 *years*	≤ 10 *years*
# cumulative top-tier universities' collaborative innovation	-0.0030^{**}	-0.0046^{**}	-0.0044^{**}	-0.0020
	(0.0014)	(0.0019)	(0.0019)	(0.0014)
# cumulative ordinary universities' collaborative innovation	-0.0097^{***}	-0.0121^{***}	-0.0105^{***}	-0.0031^{***}
	(0.0017)	(0.0022)	(0.0020)	(0.0011)
# cumulative other collaborative innovation	-0.0001	-0.0001	0.0000	0.0004
	(0.0002)	(0.0002)	(0.0003)	(0.0004)
# cumulative independent innovation	-0.0004^{***}	-0.0005^{***}	-0.0005^{***}	-0.0002^{***}
	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Population	0.1183^{***}	0.1865^{***}	0.1755^{***}	0.1310^{***}
	(0.0084)	(0.0113)	(0.0118)	(0.0088)
GDP_pc	0.0490^{***}	0.0691^{***}	0.0313^{***}	-0.0104^{*}
	(0.0065)	(0.0082)	(0.0082)	(0.0059)
Researcher	-12.7572^{***}	-40.1063^{***}	-47.2472^{***}	-2.2696
	(2.0977)	(2.9408)	(3.1783)	(2.1208)
Pub_expe	0.0594^{***}	0.0590^{***}	0.0331^{***}	-0.0136^{***}
	(0.0037)	(0.0049)	(0.0052)	(0.0033)
Tech_support	-0.0320	-0.2247^{***}	-0.7511^{***}	-0.1378^{***}
	(0.0480)	(0.0561)	(0.0530)	(0.0318)
Transport	-0.0974^{***}	-0.1295^{***}	-0.1166^{***}	-0.0369^{***}
	(0.0043)	(0.0055)	(0.0058)	(0.0040)
Constant	-1.3063^{***}	-1.7160^{***}	-1.4339^{***}	-0.8100^{***}
	(0.0744)	(0.1023)	(0.1082)	(0.0688)
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Observations	1469843	1469843	1469843	1469843
R^2	0.4997	0.7059	0.8130	0.9505

7 CONCLUSION

This study discusses the relationship between geographical proximity and industry – academia collaborative innovation. We first develop a theoretical model that incorporates the uncertainty of innovative activities and the factors that affect firm – university collaboration. The model predicts that the geographical proximity of industry – academia collaboration has an inverted U-shaped pattern with their collaborative innovations. While the decline rate of absorptive capacity will amplify this effect, the demand for knowledge diversity plays an opposite role. Our empirical results are in line with these predictions, which are based on the matched data at firm-level from the SIPO dataset, SAIC dataset, and *Amap*'s API database during 2000 – 2022. Additionally, we conduct multiple robustness checks, including using the sub-sample analysis, the alternative measures of geographical proximity and collaborative innovations, and the PPML method, to confirm that the findings remain consistent. Furthermore, we identify heterogeneous effects across different time periods, as well as geographical locations and industry characteristics. The findings suggest that pro-innovation policies amplified such effects, and geographical features and industry competition degree also serve as a source of heterogeneity. Moreover, rather than extending cooperation to other institutions, firms are more likely to retain the benefits from collaborations to avoid intra-industry competition and enhance their own market power. Although collaboration with universities significantly enhances firms' long-term survival, working with top-tier universities crowds out firms' R&D resources, which may hinder other innovative activities.

This study makes several key contributions to the literature. First, while existing studies have extensively examined the positive effect of geographical proximity on knowledge spillovers (Jaffe et al., 1993; Qiu et al., 2017), the relationship between formal R&D collaboration and geographical proximity remains vague. Our study addresses this gap by incorporating both the insights from absorptive capacity and preference for knowledge diversity in our theoretical model and empirical analysis. Second, while most studies have measured geographic influence using a single administrative unit (e.g., Fisher & Varga, 2003; Qiu et al., 2017), we calculate the firm-university distance using their longitude and latitude coordinates, thereby enabling a more accurate measurement of geographical proximity unconstrained by regional borders. Third, we examine the effects of "learning by collaboration" by exploring the effects of different rolling-window collaborations on firms' future innovation strategies, and further discuss the role of research capacity of universities and firm's long-term survival, which clarifies how post-collaboration shapes firms' competitiveness.

Although we treat the distance between firms and universities as exogenously given, which is a common approach in economics, we do not consider firms' location strategies, thereby failing to endogenize geographical distance. If future exogenous policy shocks affecting firms' location strategies occur, studies could adopt methods such as difference-in-differences (DID) to address this issue. Importantly, our finding of an inverted U-shaped relationship between geographical distance and industry – academia collaborative innovation challenges the simple notion that "closer is always better" for firm location. To some extent, this result itself alleviates the concern that proximity is merely a choice driven by unobserved strategic motives. While our findings suggest that collaboration with top-tier universities does not necessarily lead to better long-term survival for firms, because of micro-level data scarcity, we are unable to further analyze the geographical proximity threshold at which firms collaborate with ordinary universities or top-tier universities.

Despite these limitations, we believe our findings offer valuable policy implications. This study provides a novel perspective for understanding the dynamics between geographical proximity and knowledge externalities, and offers insights to how firms can leverage industry – academia collaboration to enhance their market power and competitiveness. Specifically, for policymakers, establishing dedicated innovation collaboration platforms can stimulate industry – academia partnerships. Such platforms help overcome geographical barriers, enabling firms to access and integrate a more diverse knowledge resource. For firms, it is crucial to align collaboration strategies with available resources. A firm should thoroughly assess its R&D capacity and financial constraints prior to pursing university partnerships. If its resources

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are limited, it should seek partners that match its needs, rather than aiming for top universities. It would better support its long-term growth and survival.

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Appendix

Tab. A1 – Robustness checks: sub-sample analysis based on firm's innovation experience. Source: own research

	Dependent variable: # collaborative invention patents					
	(1)	(2)	(3)	(4)	(5)	(6)
	Have invention patent		Have co-invention patent		Have co-invention patent with universities	
Proximity	3.5863**	11.2502***	3.5551**	11.1435***	3.4908**	10.9231***
	(1.5269)	(1.8534)	(1.5048)	(1.8368)	(1.4584)	(1.8061)
Proximity ^{2}		-5.4194***		-5.3647***		-5.2508***
		(1.0102)		(1.0011)		(0.9841)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Observations	90916	90916	11662	11662	3928	3928
R^2	0.2810	0.3289	0.2741	0.3215	0.2570	0.3036

Tab. A2 – Robustness checks: alternative measure of geographical proximity. Source: own research

	Dependent variable: # collaborative invention patents			
	(1)	(2)	(3)	(4)
Proximity_all	3.4803***	6.2696***		
	(0.7013)	(1.3939)		
Proximity_all ^{2}		-4.2447**		
		(1.8622)		
Proximity_perpatent			3.4852***	6.2844***
			(0.7021)	(1.3937)
Proximity_perpatent ^{2}				-4.2617**
				(1.8625)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Observations	1469843	1469843	1469843	1469843
R^2	0.2699	0.2746	0.2700	0.2748

Tab. A3 – Robustness checks: alternative measure of collaborative innovation output. Source: own research

	Dependent variable: # cumulative collaborative invention patents					
	(1)	(2)	(3)	(4)	(5)	(6)
Proximity	5.0061*	15.4494***				
	(2.6636)	(3.5804)				
Proximity ^{2}		-7.3846***				
		(1.8686)				
Proximity_all			10.8456***	23.4920***		
			(2.3508)	(5.3019)		
Proximity_all ^{2}				-19.2448***		
				(7.2484)		
Proximity_perpatent					10.8576***	23.5172***
					(2.3529)	(5.2948)
Proximity_perpatent ^{2}						-19.2736***
						(7.2425)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Observations	1469843	1469843	1469843	1469843	1469843	1469843
R^2	0.6083	0.6161	0.6220	0.6306	0.6220	0.6306

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Tab. A4 – Robustness checks: alternative measure of collaborative innovation output. Source: own research

	Dependent variable: *# collaborative invention patents*			
	(1)	(2)	(3)	(4)
	PPML		OLS (same sample as PPML)	
Proximity	37.4579***	41.8123***	3.4878**	10.9039***
	(14.0373)	(14.7941)	(1.4531)	(1.8033)
Proximity²		-18.4060***		-5.2398***
		(6.7246)		(0.9824)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Observations	3728	3728	3728	3728
R^2	0.3890	0.3958	0.2556	0.3020

Tab. A5 – Robustness checks: excluding firms located in new university town areas. Source: own research

	Dependent variable: *# collaborative invention patents*			
	(1)	(2)	(3)	(4)
	Baseline results		Excluding areas with new university town	
Proximity	3.5900**	11.2650***	3.3065**	11.1640***
	(1.5304)	(1.8559)	(1.4506)	(2.0944)
Proximity²		-5.4271***		-5.3638***
		(1.0116)		(1.1126)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Observations	1469843	1469843	1309450	1309450
R^2	0.2819	0.3299	0.2777	0.3215

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