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Artificial Intelligence and the Reconfiguration of Innovation Collaboration: Evidence from Innovation Networks in China

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Abstract: Using patent data from 284 Chinese cities over the period 2010–2022, we examine how artificial intelligence development affects inter-city innovation collaboration. We find that AI development significantly reduces collaboration through two mechanisms: a cost effect that intensifies urban specialization and raises coordination costs, and a substitution effect whereby enhanced knowledge spillovers crowd out formal partnerships. These negative effects are more pronounced for high-quality collaborations, cross-provincial partnerships, and cities in eastern China. Our findings suggest that AI reshapes the balance between autonomous innovation and formal inter-regional collaboration, with important implications for regional innovation policy.

Keywords: Artificial intelligence, Innovation collaboration networks, Knowledge spillovers, Cost effects, Substitution effects

1. Introduction

Artificial Intelligence (AI) technology is reshaping the global innovation landscape at unprecedented speed. While ChatGPT's release in late 2022 sparked widespread public attention on generative AI, the technology itself represents decades of accumulated development as a general-purpose innovation (Cockburn et al., 2018). Advances spanning from machine learning to deep neural networks have generated new industries and fundamentally altered how regional innovation networks organize. Countries worldwide have responded by elevating AI development to national priority status. China has articulated particularly ambitious goals, aiming to become a leading global AI innovation hub by 2030.

Innovation collaboration drives technological progress and economic growth in the knowledge economy. However, the implications of AI for collaboration are theoretically ambiguous because AI can reshape different types of knowledge flows in different directions. On the one hand, AI tools may reduce information search costs, improve partner matching, and expand access to codified knowledge. Recent evidence suggests that AI can substantially increase individual scientific impact while narrowing collective scientific engagement and reducing follow-on interactions among researchers (Hao et al., 2026). On the other hand, many innovation activities still depend on tacit knowledge, trust, and repeated interaction. Evidence from patent interferences shows that tacit knowledge flows remain geographically localized (Ganguli et al., 2020), while short-term visits between R&D centers can enhance invention outcomes by facilitating tacit knowledge sharing and mutual trust (Kang and Eklund, 2025). These studies suggest that AI may facilitate some forms of

knowledge access while weakening or substituting for other forms of formal collaboration.

This distinction helps explain why the literature has not reached a unified conclusion on whether AI promotes or inhibits inter-city innovation collaboration. The effect of AI depends on whether collaboration relies mainly on codified knowledge or tacit interaction, whether partners possess similar or complementary knowledge bases, and whether cities have sufficient absorptive capacity to transform external knowledge into formal joint innovation. Digital work environments may reduce the friction of distance, as shown in software developer networks, but colocation still matters for collaboration frequency (Goldbeck, 2025). Similarly, reductions in connection costs can alter team formation and help inventors match with more productive distant partners (Bernard et al., 2025). These findings imply that AI may create new opportunities for cities with weaker technological bases to access external knowledge, while the translation of such opportunities into formal joint innovation remains contingent on local capabilities and inter-city coordination.

Accordingly, this paper focuses on formal, codified, and legally recorded inter-city innovation collaboration, measured by joint patent applications. This empirical scope allows us to examine whether AI development changes formal collaboration networks recorded in patent data, while recognizing that open-source projects, platform-based knowledge sharing, remote development, and informal knowledge exchange are also important channels of innovation collaboration. Because these non-patent forms of collaboration are not directly observable in our data, we now acknowledge this limitation explicitly in the discussion section. The empirical question is therefore not whether AI promotes or inhibits all forms of collaboration, but whether AI development weakens formal inter-city innovation ties in a setting where alternative channels of knowledge access become increasingly available.

This paper draws on patent data from 284 prefecture-level and above cities in China over the period 2010–2022 to construct inter-city innovation collaboration networks and systematically examine how AI development affects such collaboration[1]. The findings indicate that AI development significantly reduces inter-city innovation collaboration. Mechanism analysis reveals two primary channels: a cost channel, whereby AI-driven increases in urban specialization and centralization raise coordination costs and information asymmetries; and a substitution channel, through which AI expands the efficiency and reach of knowledge spillovers, allowing informal knowledge exchange to crowd out formal collaborative arrangements. Heterogeneity analysis further shows that this dampening effect is more pronounced for high-quality collaborations, cross-provincial partnerships, collaborations among eastern cities, and inter-firm collaboration.

[1] This measure does not capture all forms of collaboration in the AI era. Open-source communities, model-sharing platforms, algorithm competitions, remote software development, contract research, consulting, and informal knowledge exchange may also constitute important channels of knowledge collaboration, but they are not directly observable in the city-pair patent data used in this study. The empirical question is therefore whether AI development is associated with changes in formal patent-based inter-city collaboration, rather than whether AI promotes or inhibits every possible form of innovation collaboration.

These findings carry important policy implications. The inhibitory effect of AI development on inter-city innovation collaboration is counterintuitive: technological progress enhances individual innovation efficiency while simultaneously weakening incentives for inter-agent collaboration. This pattern cautions against viewing technological change as having linear effects on the economy, and against the assumption that new technologies necessarily generate positive network externalities. If AI development systematically undermines collaboration networks, innovation activities may become increasingly fragmented, impeding breakthroughs that require the integration of knowledge from multiple domains. AI policy must therefore move beyond a purely technology-centric orientation to incorporate the resilience and connectivity of regional innovation networks into policy evaluation frameworks.

This study contributes to the literature along two dimensions. It advances understanding of AI's economic effects by shifting the focus from firm-level outcomes to the meso-level structure of innovation networks. Prior work has documented how AI adoption influences firm growth, productivity, and patenting activity (Acemoglu and Restrepo, 2018; Rammer et al., 2022; Babina et al., 2024), yet these studies largely treat innovation as an individual or organizational outcome. As the knowledge frontier expands and the "burden of knowledge" grows heavier (Jones, 2009), collaboration networks have become critical channels for accessing the complementary knowledge assets required for breakthrough innovation (Powell et al., 1996). By examining how AI development reshapes inter-city collaborative ties, this paper identifies a reconfiguration of regional innovation organization, in which stronger autonomous innovation capacity may coexist with weaker formal inter-city collaboration, a tension that has received limited attention in the literature on technology and regional innovation.

The paper also develops an integrated analytical framework linking AI development to inter-city collaboration through cost and substitution mechanisms. Existing research has separately examined how technological complexity raises coordination costs (Jones, 2009), how spatial concentration generates digital divides (Frank et al., 2019), and how knowledge spillovers substitute for formal partnerships (Griliches, 1992). These insights, however, have not been synthesized into a unified framework for understanding AI's impact on collaborative structures. By integrating classical concepts—the "burden of knowledge", "absorptive capacity" (Cohen and Levinthal, 1990), and "cognitive distance" (Nooteboom et al., 2007)—this study provides a theoretical structure capable of explaining how a single technological shock can simultaneously enhance local innovation capacity while disrupting the broader architecture of regional innovation systems.

The remainder of this paper proceeds as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data and empirical strategy. Section 4 presents the results, including baseline estimates, heterogeneity analysis, and mechanism tests. Section 5 concludes.

2. Literature and Hypothesis

2.1. Literature Review

2.1.1. Innovation network theory

Robust regional innovation networks not only facilitate collaborative innovation but also accelerate the circulation of specialized knowledge within regions (Boschma and Ter Wal, 2007). When knowledge bases become complex and dispersed, network ties serve as critical channels through which organizations access complementary assets (Powell et al., 1996). Rather than pursuing innovation independently, firms benefit from adopting appropriate open innovation strategies that leverage external collaboration to compensate for internal resource constraints (Dahlander and Gann, 2010). Open innovation, however, embodies an inherent tension: the creation of new knowledge requires openness to external sources, yet commercialization demands protection against knowledge spillovers (Laursen and Salter, 2014). Regarding the mechanisms underlying inter-firm innovation collaboration, Ahuja (2000) highlights the decisive role of network structural position in shaping both collaboration propensity and innovation performance. At the regional level, Yokura et al. (2013) examine joint research projects in Japan and find that innovation network formation depends on R&D technologies, participating actors, and multiple dimensions of proximity—including technological and institutional proximity.

2.1.2. AI development and innovation

The widespread application of artificial intelligence has ushered in a new era of innovation, emerging as a key engine for fostering innovation and generating new productive forces. Recent studies have increasingly examined AI not only as an automation technology, but also as a general-purpose technology that may reshape the process of invention itself (Crafts, 2021). Existing research has documented AI's effects on innovation using industrial robot data (Liu et al., 2020; Acemoglu and Restrepo, 2018), employee skill structures and job postings (Babina et al., 2024), survey data (Rammer et al., 2022), and firm-level measures of AI capabilities. Babina et al. (2024) show that AI investment can promote firm growth through product innovation, while Wang and Wu (2025) further emphasize that AI's innovation effects depend on the match between AI capabilities and organizational processes. These studies suggest that AI affects innovation not only by improving production efficiency, but also by changing how firms search for opportunities, recombine knowledge, and organize product development.

A more recent strand of research also shows that AI tools may reshape knowledge production and collaboration patterns. Hao et al. (2026), for example, find that AI tools expand individual scientists' impact while narrowing collective scientific focus and reducing follow-on engagement among researchers. Evidence from digital collaboration settings similarly suggests that digital work environments can reduce geographic friction without eliminating the importance of colocation and organizational conditions (Goldbeck, 2025). These findings are relevant to the present study because

they show that AI may simultaneously expand access to external knowledge and alter the incentives for formal collaboration. Consistent with the research question and data structure of this paper, our analysis focuses on the broader development of AI technology rather than on the separate effects of any single recent AI application. Specifically, this paper examines how general AI technological development affects formal inter-city innovation collaboration recorded in joint patent applications.

2.1.3. Knowledge spillover and proximity

Geographic proximity has been established as a critical factor in knowledge spillover research. Defined as the spatial closeness among economic agents, geographic proximity constitutes the most fundamental dimension of the proximity framework (Boschma, 2005). Krugman (1991) observed that knowledge travels more easily across corridors than across highways, highlighting how spatial distance impedes knowledge transmission—a finding corroborated by extensive empirical evidence (Jaffe et al., 1993; Audretsch and Feldman, 1996). The literature documents pronounced distance-decay patterns in the relationship between geographic proximity and knowledge spillovers (Kerr and Kominers, 2015; Matray, 2021). Administrative and institutional boundaries also shape knowledge flows: although geographic proximity facilitates spillovers, administrative and institutional borders remain significant barriers to cross-regional knowledge transmission (Ponds et al., 2010), offering an important lens for understanding regional innovation disparities.

2.2. Research Hypothesis

The evolution of innovation collaboration networks fundamentally reflects rational agents weighing the costs and benefits of collaboration; stable, efficient partnerships emerge only when benefits exceed costs. Cross-city collaboration typically confronts multifaceted pressures, including transaction and knowledge costs (Vivona et al., 2023). According to transaction cost theory (Williamson, 1979), when in-house R&D costs fall below the costs of collaborative development, organizations may prefer independent innovation. Although AI development enhances cities' overall innovation capacity, the resulting intensification of specialization and centralization may substantially raise the costs of inter-city collaboration, thereby suppressing cooperative activities.

From a specialization perspective, AI technology propels urban innovation toward higher levels of specialization, a process that increases coordination and communication costs in inter-city partnerships. As AI applications continuously expand the technological frontier, the "burden of knowledge" grows heavier and required expertise becomes increasingly subdivided (Jones, 2009). When different cities deepen their AI development along distinct technological paths and specialized directions, technical vocabularies and knowledge systems diverge, gradually giving rise to relatively independent specialized technological ecosystems. According to cognitive distance theory, although some degree of difference benefits innovation, excessive cognitive distance leads to comprehension difficulties and communication failures (Nooteboom et al., 2007). Innovation actors tend to seek partners within similar domains to maximize protection of their interests and

mitigate opportunistic behavior; social proximity establishes trust and reduces opportunism risk (Boschma, 2005). When highly specialized cities attempt to collaborate, the matching costs and additional coordination costs arising from specialization differences often exceed expected collaboration benefits, thereby impeding inter-city innovation partnerships.

From a centralization perspective, AI development depends heavily on high-skilled labor, advanced technical knowledge, and sophisticated infrastructure—key factors that typically concentrate in technologically advantaged hub cities, creating pronounced spatial agglomeration (Frank et al., 2019). Large cities attract factor accumulation through sharing, matching, and learning mechanisms, generating self-reinforcing agglomeration effects (Duranton and Puga, 2004). This dynamic produces a siphoning effect on technologically underdeveloped regions, establishing a distinct core-periphery technological division and widening the inter-regional "digital divide" (Van Dijk, 2020). Such patterns elevate information asymmetries and capability-matching costs in the collaboration process. Hub cities, concerned with protecting competitive advantages, guard against the outflow of core technologies and critical knowledge. Peripheral cities, constrained by limited "absorptive capacity" (Cohen and Levinthal, 1990), often lack the foundations necessary for participating in high-level technological partnerships and struggle to effectively assimilate and utilize advanced technologies from hub cities. Information uncertainty and asymmetry delay optimal collaboration timing, increase the complexity and uncertainty of partnership negotiations, and raise monitoring, coordination, and risk-management costs—all of which adversely affect inter-city innovation collaboration.

Based on the foregoing analysis, this paper proposes Hypothesis 1:

AI development intensifies urban specialization and centralization, increases innovation collaboration costs, and thereby suppresses inter-city innovation collaboration[1].

AI development may also alter inter-city collaboration by changing the relative value of formal collaboration and informal knowledge access. We retain the concept of a substitution effect, but define it more precisely as a conditional reduction in cities' reliance on formal, legally recorded collaboration when AI expands access to external knowledge through less formal channels. This substitution effect should not be understood as a mechanical or universal displacement of formal collaboration. Its strength depends on the type of knowledge involved, the degree of technological distance between cities, and the absorptive capacity of potential partners. Codified knowledge can be searched, recombined, and transmitted more easily when AI improves information retrieval and knowledge matching. By contrast, tacit knowledge still requires trust, repeated interaction, and

[1] Micro-level evidence lends support to this hypothesis. Huawei's internal documents, for instance, articulate a strategic objective of "building fully autonomous and controllable AI infrastructure," with explicit emphasis on end-to-end, full-stack capabilities spanning chips to cloud services and hardware to software. This vision has guided a fundamental reorientation of the firm's R&D strategy—from early reliance on external partnerships toward a model in which in-house development takes precedence and collaboration plays a subordinate role. Accordingly, external technology partnerships have become subject to increasingly stringent regulatory scrutiny within the firm. The pattern exemplifies the cost channel: once a firm acquires comprehensive AI capabilities, the coordination costs of external collaboration rise relative to the declining marginal costs of internal development.

sufficient cognitive proximity. Recent evidence shows that short-term R&D visits can improve invention outcomes by facilitating tacit knowledge sharing, but that such benefits are strongest at intermediate knowledge distance (Kang and Eklund, 2025). Similarly, different forms of proximity shape the formation of research collaboration in conditional ways (D'Este et al., 2013). These findings suggest that expanded knowledge access may either complement formal collaboration or generate a substitution effect, depending on the collaboration context.

AI development has fundamentally transformed both the efficiency and accessibility of knowledge spillovers[1]. Machine learning, natural language processing, and related AI technologies have dramatically expanded the breadth and depth of urban knowledge search; extending search scope and deepening search intensity both enhance innovation performance (Laursen and Salter, 2006). Agrawal et al. (2018) argue that AI's core economic property is the reduction of prediction costs, rendering the retrieval, identification, and recombination of existing knowledge from massive datasets extraordinarily efficient. Through intelligent patent analysis and literature mining, cities can more precisely and efficiently track technological dynamics and innovation outputs from other cities, reducing dependence on formal collaboration. AI also facilitates cross-firm and cross-sector technological learning through intelligent learning and imitation, expanding the scope of knowledge externalities (Aghion et al., 2018). This effectively breaks down traditional temporal, spatial, and institutional barriers to knowledge transmission, enabling spillovers to traverse geographic and administrative boundaries more readily and flow over long distances, promoting precise knowledge matching and combination while lowering matching and transaction costs. When spillover efficiency and coverage improve markedly, cities can "free ride" to acquire external knowledge, dramatically reducing redundant research costs[2]. Consequently, urban actors increasingly favor "informal collaboration"[3].

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[1] Recent advances in AI applications have further changed the background against which inter-city innovation collaboration takes place. These developments may lower the cost of searching, interpreting, and recombining external knowledge, and they may create new channels for remote or informal collaboration. However, these forms of collaboration are not directly observable in our city-pair patent data, nor does our empirical design identify the separate effects of specific recent AI applications. Accordingly, we treat these developments as important contextual changes rather than as separate empirical outcomes. The focus of this study remains formal, codified, and legally recorded inter-city innovation collaboration, measured by joint patent applications. This empirical scope allows us to examine whether the broader development of AI technology reshapes formal collaboration networks, while acknowledging that non-patent forms of collaboration constitute an important limitation and a direction for future research.

[2] In the setting examined here, we focus on formal inter-city collaboration recorded through joint patent applications. AI may generate a substitution effect when external knowledge becomes more accessible through patent disclosure, literature mining, technology tracking, and other forms of knowledge spillover, thereby reducing cities' marginal need to establish formal joint patenting arrangements. This does not mean that informal knowledge flows are always superior to formal collaboration, nor that all collaboration declines. Rather, it implies that AI may weaken the marginal need for legally recorded joint innovation when cities can obtain, screen, and recombine external knowledge through less formal channels. This logic is especially relevant when formal collaboration entails high coordination, negotiation, and knowledge-management costs (Vivona et al., 2023).

[3] Research publications can function as powerful conduits for knowledge diffusion—a dynamic that Google's experience vividly illustrates. As a global leader in AI technology, the company published nearly 500 AI research papers since 2019. Yet as competitors rapidly narrowed the technological gap by capitalizing on the very

The intensity of this substitution effect is further shaped by the institutional environment, particularly intellectual property protection levels. Excessively strong IP protection forces innovators to pay substantial royalties during R&D and causes patent approval delays that reduce innovation efficiency (Shapiro, 2001). The "tragedy of the anti-commons" proposed by Heller and Eisenberg (1998) suggests that excessive property fragmentation may impede subsequent innovation integration. Overly strong IP protection can also generate monopoly effects: supernormal profits from over-licensing foster "innovation inertia" among collaborating parties and increase the difficulty of accessing new technologies from the knowledge pool for innovation partnerships. Galasso and Schankerman (2015) provide causal evidence that patent rights impede downstream innovation in computing and electronics; patent invalidation increases subsequent citations by 50 percent. By contrast, enhanced knowledge spillovers raise innovators' opportunities and efficiency in acquiring knowledge through relatively straightforward procedures, and AI makes such knowledge acquisition even more efficient and convenient. In regions with stringent IP protection, the substitution of informal for formal collaboration is therefore more pronounced.

Based on this analysis, this paper proposes Hypothesis 2:

AI development expands cities' access to external knowledge and produces a substitution effect that reduces reliance on formal inter-city innovation collaboration; this substitution effect is expected to be stronger when formal collaboration faces greater institutional and coordination constraints.

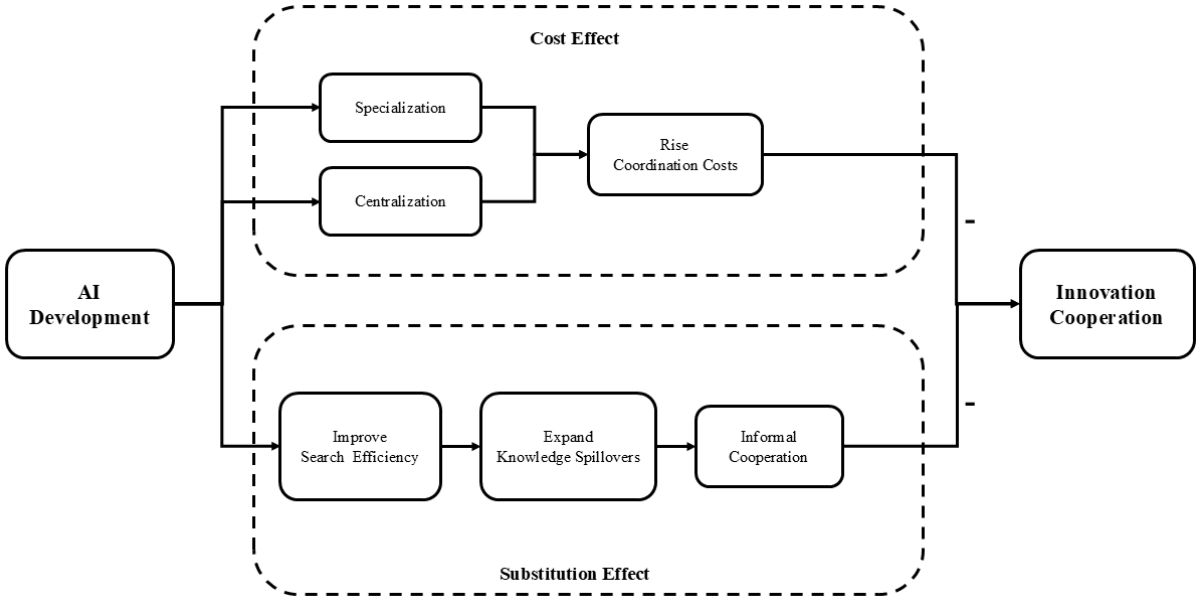


Figure 1. The conceptual framework of AI development on innovation collaboration

knowledge these publications disclosed, Google came to recognize the strategic risks of excessive spillovers. Beginning in 2023, the company shifted to a policy of withholding research findings until they had been translated into commercial products.

3. Empirical Specification

3.1. Regression Model

To test whether AI development significantly affects inter-city innovation collaboration, the following econometric model is specified:

$$collaboration_{ijt} = \beta \times AITech_{ijt} + Control_{ijt} \times \delta + \gamma_i + \gamma_j + \eta_t + \epsilon_{ijt} \quad (1)$$

where $collaboration_{ijt}$ denotes innovation collaboration between cities i and j in year t. $AITech_{ijt}$ measures the level of AI technology development in the two cities in year t. $Control_{ijt}$ denotes a row vector of control variables. γ_i, γ_j, and η_t represent city fixed effects and year fixed effects, respectively. ϵ_{ijt} denotes the error term.

3.2 Data and Sample

The sample spans 2010–2022 and draws on three data sources. Patent data are obtained from the China National Intellectual Property Administration and contain multidimensional patent information, including patent type (invention application, utility model, design), applicant information, and technology classification. Business registration data from the State Administration for Industry and Commerce record firm registration details—including firm name and registered address—used to geocode patent applicants. City-level economic data from the annual China City Statistical Yearbook are employed in robustness analyses to construct city-level control variables[1]. Because innovation collaboration fundamentally involves knowledge exchange and interaction among inventors across regions—and, unlike citation-based measures, does not permit directional identification of knowledge flows—the sample is constructed at the city-pair level. For each year, all possible pairings of 284 cities are enumerated, retaining only the upper-triangular elements of the pair matrix (excluding diagonal elements). This yields an undirected, non-duplicated sample of over 40,000 city pairs.

Innovation collaboration ($collaboration$). Innovation collaboration is measured by the frequency of joint patent applications between cities. This measure captures formal patent-based inter-city collaboration: it records cases in which applicants located in different cities jointly file a patent application and therefore leave a codified, legally traceable record of collaborative inventive activity. Patent-based collaboration measures have been widely used to study inventor networks and collaborative knowledge creation because they provide standardized information on applicants, locations, technologies, and filing years (Crescenzi et al., 2016). This feature is particularly important for the present city-pair setting, where the dependent variable requires consistent and replicable measurement across all city pairs and years.

The construction proceeds as follows. Patents with two or more applicants are first identified and extracted from the patent database to ensure the sample captures collaborative activity. Given

[1] Missing data for certain years or cities were imputed.

the difficulty of obtaining address information for individual applicants and data completeness requirements, the analysis is restricted to patents where all applicants are corporate entities, ensuring accuracy and feasibility in subsequent address matching. For each applicant in the filtered sample, a fuzzy matching algorithm links applicant names in the patent data to firm names in the business registration database, yielding detailed address information that is then parsed to identify province and city. Patent-level collaboration information is aggregated to the city level, calculating the total frequency of joint patent applications between any two cities within each period and constructing an upper-triangular matrix of inter-city innovation collaboration frequencies[1].

This operationalization has a clear measurement boundary. Joint patent applications do not capture non-patent forms of collaboration, such as open-source projects, pre-trained model sharing, algorithm competitions, remote collaborative development, contract research, consulting, or informal knowledge exchange. Prior research has shown that innovation collaboration and knowledge transfer may occur through multiple channels beyond patents and commercialization (Perkmann et al., 2013), and that non-patent knowledge accumulation can account for a substantial share of innovation returns (Chen et al., 2021). We therefore interpret the dependent variable as a measure of formal patent-based collaboration rather than a measure of all real knowledge collaboration among cities.

AI development is measured using AI patent applications for each city pair over a specified period. AI-related patents are first identified and extracted based on IPC codes following the Key Digital Technology Patent Classification System (2023) published by the China National Intellectual Property Administration. Two measurement considerations inform the construction of this variable. Patent stocks over a given period more accurately reflect cumulative technological development than contemporaneous flows, while excessively dated patents fail to represent current technological conditions due to technological obsolescence. Patent applications also exhibit substantial time lags from filing through grant to market commercialization; using contemporaneous patent counts would therefore introduce measurement error. Accordingly, AI development for each city in a pair is measured as the cumulative sum of AI patent applications over the preceding two to six years relative to the current year. This specification captures both the stock nature of technological development and technological iteration cycles while mitigating lag effects between patent application and technology commercialization.

Control variables. The analysis controls for a set of characteristic variables for each city within the city pair, including: (1) Economic development level ($lnpergdp$). Economic development strongly influences a city's innovation capacity and collaborative propensity. Cities with similar development levels are more likely to form stable cooperative relationships. It is measured by the natural logarithm of per capita GDP for the current year. (2) Urbanization level ($urban$).

[1] For patents with N applicants, it is assumed that all applicants collaborated pairwise, resulting in a collaboration frequency of $N \times (N-1)/2$ for the patent.

Urbanization indicates a city's modernization and infrastructure quality, affecting the aggregation and mobility of innovation factors. It is calculated as the ratio of built-up area to administrative area. (3) Industrial structure ($industry$). Variations in industrial structure influence technological demand alignment and complementarity between cities. Cities with a larger service sector share generally show a stronger tendency for innovation collaboration. It is measured by the ratio of tertiary to secondary industry output. (4) Innovation level ($lnpatent$). Innovation capacity and foundation are crucial determinants of effective intercity collaboration. Cities with comparable innovation capacities tend to form mutually beneficial partnerships. This variable is measured as the logarithm of total patent applications. Table 1 presents descriptive statistics for all variables.

Table 1. Descriptive statistics of key variables

Variables	Obs.	Mean	Std. Dev.	Min.	Max.	Med.
collaboration	47677	1.65	1.54	.00	8.50	1.39
AITech	47677	9.38	1.69	2.08	13.39	9.47
lnpergdp_1	47677	2.23	.75	-.66	3.97	2.28
lnpergdp_2	47677	2.01	.71	-.51	3.97	1.98
urban_1	47677	.06	.08	.00	.48	.03
urban_2	47677	.04	.07	.00	.48	.02
industry_1	47677	1.49	.95	.11	5.93	1.19
industry_2	47677	1.21	.58	.18	5.93	1.11
lnpatent_1	47677	9.60	1.70	2.71	12.67	9.76
lnpatent_2	47677	9.20	1.60	2.71	12.67	9.22

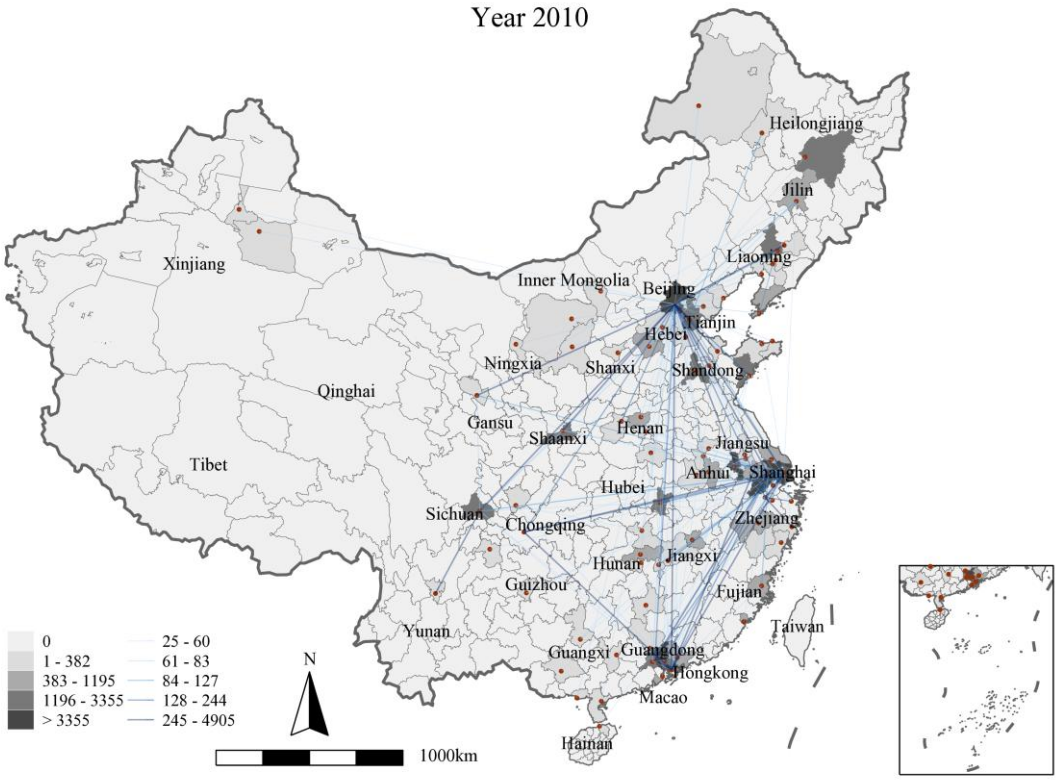
Note: The numbers 1 and 2 following the variable names represent the two cities in the city pair, respectively.

Figure 2 illustrates the spatial distribution of AI development and inter-city innovation collaboration in 2010 and 2022. Both dimensions experienced substantial growth over this period. More cities adopted AI technologies, and a larger number of city pairs engaged in collaborative innovation. A structural decomposition, however, reveals that the relationship between these two trends is not straightforwardly positive. AI technology levels rose markedly across many cities, with the eastern and central regions exhibiting the most pronounced increases. By 2022, over 35 percent of cities had attained AI development indices exceeding 383, following the measurement approach described above. This count excludes leading technology hubs such as Beijing, Shanghai, and Hangzhou, which had already achieved substantial AI capacity by 2010.

The evolution of the collaboration network tells a different story. Although overall network density increased, polarization intensified concurrently. When collaboration ties are weighted by frequency, a distinctive cross-shaped structure emerges. This configuration comprises four dominant node clusters: Beijing in the north; Shanghai and Hangzhou in the east; Shenzhen and Guangzhou in the south; and Chengdu and Chongqing in the west. These clusters maintain dense interconnections among themselves while simultaneously serving as the primary collaboration

targets for most other cities.

The geographic patterns thus present a striking disconnect. AI adoption has diffused across a broad spatial range, yet collaborative innovation has not expanded commensurately. Instead, collaboration has become increasingly concentrated around a small number of hub cities. This divergence suggests that the aggregate effect of AI development on inter-city innovation collaboration is likely negative.



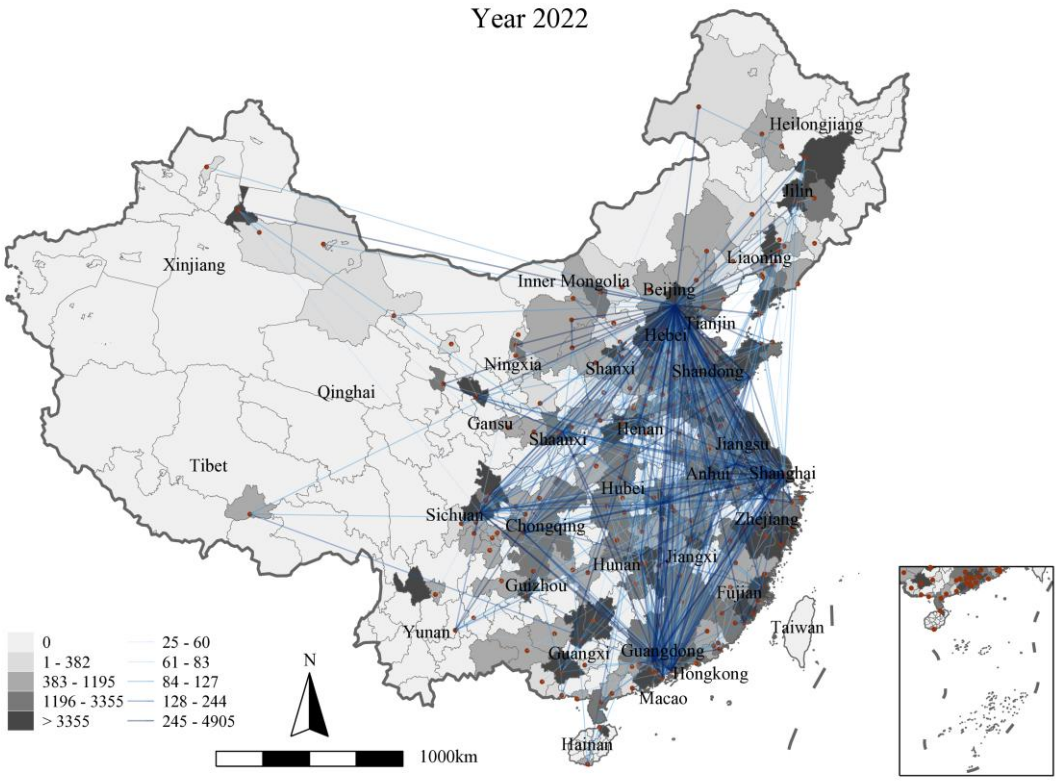


Figure 2. Distribution of AI development and innovation collaboration among cities in China

4. Empirical Results

4.1. Benchmark regression

Table 2 reports the baseline regression results examining the impact of artificial intelligence technology development on inter-city innovation collaboration. Column (1) presents results without controlling for fixed effects or covariates, showing a significant positive effect of AI technology development on inter-city innovation collaboration. Columns (2) through (4) progressively incorporate control variables, city fixed effects, and both city and year fixed effects. Across these specifications, the coefficient on the core explanatory variable *AITech* is negative and statistically significant at the 1% level, indicating that after accounting for omitted variable bias, AI technology development significantly inhibits inter-city innovation collaboration.

Table 2. The impact of AI technology development on intercity innovation collaboration

	(1)	(2)	(3)	(4)
AITech	0.368***	-0.124***	-0.569***	-0.663***
	(0.010)	(0.017)	(0.020)	(0.022)
Control	N	Y	Y	Y
City FE	N	N	Y	Y
Year FE	N	N	N	Y
Observations	47820	47683	47677	47677
Adjusted R^2	0.16	0.26	0.38	0.39

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors, clustered at the city-pair level,

are reported in parentheses. All regressions include a constant term, which is omitted here for brevity. The same convention applies below unless stated otherwise.

The development level of AI technology may not be randomly distributed but rather influenced by geographic location, infrastructure quality, and external policy shocks, potentially generating self-selection bias. Not all city pairs engage in innovation collaboration—some cities may forgo participation due to resource constraints, policy orientation, or geographic factors—introducing sample selection bias. To address these concerns, we employ the Heckman two-stage model. The first stage uses a Probit model to estimate the probability of innovation collaboration between city pairs, incorporating the following exclusion restrictions: (i) distance ($distance$), the straight-line distance (km) between the two cities; (ii) across-province indicator ($across\ province$), coded 1 if the cities are in different provinces and 0 otherwise. The inverse Mills ratio (IMR) is then computed, with results reported in Column (2) of Table 3. The second stage incorporates the IMR into the baseline regression to mitigate selection bias arising from non-random behavior. Column (2) of Table 3 shows that after accounting for sample selection, the coefficient on *AITech* remains significantly negative at the 1% level, confirming the robustness of our findings to selection concerns.

Beyond selection bias, reverse causality poses an additional endogeneity concern: inter-city innovation collaboration may influence AI technology development levels, thereby biasing coefficient estimates. We employ an instrumental variable approach to address this issue and further validate our baseline results. For each city in a city pair, we construct an instrument by interacting the city's 2005 ratio of computer and software industry employment to total population—a measure of initial technological endowments—with its cumulative AI patent stock. We then sum these interaction terms across both cities in each pair and take the logarithm. Cities with larger computer industries in 2005 typically possessed greater human capital, financial resources, and technological capabilities that subsequently shaped AI development trajectories, satisfying the relevance condition. The temporal distance from 2005 to the sample period makes it implausible for this historical measure to directly affect contemporary inter-city innovation collaboration, satisfying the exclusion restriction.

Columns (3) and (4) of Table 3 report two-stage least squares (2SLS) estimates. The first-stage coefficient is significant at the 1% level. The Kleibergen-Paap rk Wald F-statistic exceeds the critical value at the 10% level, indicating that the instrument passes the weak identification test and ruling out weak instrument concerns. The second-stage results confirm that the coefficient on AITech remains significantly negative at the 1% level, providing further evidence that AI technology development exerts a significant inhibitory effect on inter-city innovation collaboration.

Table 3. Endogeneity test results

	Heckman Two-stage Model		IV-2SLS	
	(1)	(2)	(3)	(4)

	First stage	Second stage	First stage	Second stage
AITech	-0.208***	-0.668***		-1.286***
	(0.007)	(0.023)		(0.127)
AITech_IV			12.748***	
			(1.278)	
distance	-0.402***			
	(0.007)			
across province	-0.961***			
	(0.016)			
IMR		-0.516***		
		(0.034)		
Control	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	556829	47813	46771	46771
Adjusted R^2		0.40		
F-Statistics			99.49	

The baseline regression results indicate that AI technology development significantly suppresses intercity innovation collaboration. To mitigate potential confounding effects, a series of robustness checks is conducted to assess the stability of the estimates. First, the core dependent variable is remeasured as the ratio of intercity collaboration frequency to total patent applications in the current year. Second, to address potential measurement error, the core explanatory variable is alternatively measured as the ratio of the two cities' AI technology stock to total patent applications in the current year. Third, the empirical specification is augmented by incorporating city-by-year interaction fixed effects, in addition to city and year fixed effects, to control for city-specific time-varying factors. Moreover, given that the COVID-19 outbreak in 2020 severely restricted mobility and temporarily slowed AI research and development, observations from 2020 onward are excluded to minimize pandemic-related distortions. Finally, because centrally administered municipalities differ markedly from prefecture-level cities in administrative status, policy environment, economic development, and AI capacity, the analysis is repeated after excluding these municipalities. Table 4 reports the robustness check results, all of which consistently support the baseline finding that AI technology development significantly inhibits intercity innovation collaboration.

Table 4. Robustness

	(1) Replacing the measurement of the dependent variable	(2) Replacing the measurement of the explanatory variable	(3) Controlling for high-dimensional fixed effects	(4) Controlling for additional factors	(5) Excluding the impact of the COVID-19 pandemic	(6) Excluding centrally administered municipalities
AITech	-0.072***	-1.414***	-0.766***	-0.563***	-0.714***	-0.520***
	(0.007)	(0.109)	(0.025)	(0.023)	(0.029)	(0.026)
Control	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	47677	47677	46979	47677	28908	39342

Adjusted R^2	0.15	0.34	0.38	0.47	0.38	0.24

4.2. Heterogeneity

The preceding analysis examines the impact of AI technology development on intercity innovation collaboration and conducts a series of robustness checks, providing robust evidence that AI technology development significantly suppresses intercity innovation collaboration. This section further investigates the heterogeneous effects of AI technology development on intercity innovation collaboration from four dimensions: AI technology types, forms of intercity collaboration, spatial positions of collaborating cities, and types of collaborating entities. The heterogeneity analysis is used to examine whether the estimated negative association varies across collaboration contexts in ways that are consistent with the proposed mechanisms. We do not interpret these subgroup patterns as separate causal-channel tests. Rather, they help assess whether AI's association with formal collaboration is stronger when collaboration is more knowledge-intensive, spatially distant, exposed to regional capability gaps, or shaped by stronger competitive incentives. This distinction is important because AI may reduce some collaboration costs while increasing others. For example, lower information search costs may help cities identify distant partners, but greater technological distance, weaker absorptive capacity, and stronger knowledge-protection incentives may still make formal joint patenting less attractive.

According to the Classification System of Key Digital Technology Patents (2023) issued by the China National Intellectual Property Administration, AI technologies are categorized into three primary groups: AI hardware platforms centered on intelligent chips, AI general technologies dominated by machine learning, and AI core technologies focused on language processing. Different types of AI technologies may exert heterogeneous effects on intercity innovation collaboration. Accordingly, this study disaggregates AI technologies into platform ($AITech_platform$), general ($AITech_general$), and core technologies ($AITech_core$), and examines the effect of each subcategory on intercity innovation collaboration. The results reported in Table 5 show that the effects of different AI sub-technologies on intercity innovation collaboration are largely similar, and all are significantly negative. A possible explanation is that, although these sub-technologies differ in their specific applications, the AI knowledge system is highly interconnected, exhibits limited internal heterogeneity, and is structurally cohesive. Consequently, these AI sub-technologies generate comparable effects on intercity innovation collaboration.

Table 5. Effects of different types of AI technology on collaboration

	(1)	(2)	(3)
AITech_platform	-0.591***		
	(0.020)		
AITech_general		-0.661***	
		(0.022)	
AITech_core			-0.654***
			(0.022)

Control	Y	Y	Y
City FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	47676	47677	47677
Adjusted R^2	0.38	0.39	0.38

China's innovation patents can be classified into invention patents and non-invention patents, the latter including design patents and utility model patents, according to differences in R&D complexity, innovation intensity, and technological content. Invention patents exhibit higher innovativeness and technological sophistication, longer development cycles, and greater R&D difficulty, whereas non-invention patents are characterized by lower innovation intensity, shorter development periods, and reduced R&D difficulty. Based on these distinctions, this study uses patent types as proxies for the quality of intercity innovation collaboration and conducts separate regressions after recalculating collaboration frequencies by patent category to examine the effects of AI development across different quality levels of collaboration. As shown in columns (1) and (2) of Table 6, AI development significantly suppresses both types of innovation collaboration, with a stronger negative effect on higher-quality collaboration. High-quality innovation collaboration is more likely to occur among cities with similarly strong innovative capacities; however, AI development further widens regional technological and economic disparities, limiting the ability of less innovative cities to engage in high-quality collaboration with leading cities and reducing such opportunities. By contrast, low-quality intercity innovation collaboration typically involves lower technological barriers and weaker reliance on AI, suggesting that AI development exerts a stronger suppressive effect on high-quality collaboration than on low-quality collaboration.

In addition, to examine whether AI development affects intercity collaboration beyond the AI domain—namely, the existence of inter-technology spillover effects—this study classifies collaborative innovation patents into AI and non-AI categories, recalculates intercity collaboration frequencies, and conducts subsample regressions. As shown in columns (3) and (4) of Table 6, AI development significantly suppresses intercity innovation collaboration in both AI and non-AI domains, with no statistically significant difference between them. Innovation collaboration in AI and non-AI fields is not fully independent; instead, the two domains are interrelated, and AI development may generate spillover effects on non-AI activities. These interconnections suggest that innovation collaboration in both domains is likely to be influenced in similar ways, leading to only modest differences in the magnitude of the suppressive effects.

Table 6. Effects of AI development on different fields of collaboration

	(1)	(2)	(3)	(4)
	Invention Patents	Non-invention Patents	The AI domain	The non-AI domain
AITech	-0.660***	-0.537***	-0.682***	-0.607***
	(0.024)	(0.024)	(0.032)	(0.022)
Control	Y	Y	Y	Y
City FE	Y	Y	Y	Y

Year FE	Y	Y	Y	Y
Observations	39823	33061	19845	44371
Adjusted R^2	0.40	0.34	0.43	0.36

Table 7 reports the heterogeneous effects of AI development on cross-regional innovation collaboration, based on a sample stratified by the provinces of the collaborating cities. The results indicate that the negative effect of AI development on intercity innovation collaboration intensifies with geographic distance and is most pronounced in cross-provincial collaboration, whereas this effect is partially mitigated after excluding core cities [1]. As geographic distance between collaboration partners increases, the positive spatial spillovers of AI development weaken, intercity information-processing costs rise, and disparities in AI development and factor endowments across cities become more pronounced. This pattern is particularly evident in collaboration with cross-provincial core cities, where innovation factors tend to concentrate in more developed cities, causing the "siphoning effect" to outweigh positive technological spillovers. In addition, core cities typically exhibit stronger intellectual property protection, which further raises the barriers to intercity innovation collaboration. Consequently, greater geographic distance amplifies the inhibitory impact of AI development on intercity innovation collaboration, with this adverse effect being particularly pronounced in collaborations involving cross-provincial core cities.

Table 7. Effects of AI development on cross-regional innovation collaboration

	(1) Within the same province	(2) Across provinces	(3) Across provinces (excluding core cities)
AITech	-0.408***	-0.755***	-0.579***
	(0.066)	(0.021)	(0.024)
Control	Y	Y	Y
City FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	7040	40607	30844
Adjusted R^2	0.63	0.47	0.27

Similarly, after stratifying the sample by the regions of the collaborating cities, Figure 3 presents the regression coefficients of the core explanatory variable, with the dashed line indicating the baseline estimate. Specifically, among collaborations involving eastern, central, and western cities, the suppressive effect of AI development is strongest for east–west interregional collaboration and weakest for collaboration within the central region. China's AI development exhibits substantial regional disparities: the eastern region leads with clear technological advantages and rapid growth, whereas the western region lags behind and benefits less from AI development. Innovation collaboration between eastern and western cities typically entails higher coordination and

[1] Based on the total number of AI patent applications, the five cities with the highest levels of AI technological development are Beijing, Shanghai, Guangzhou, Hangzhou, and Shenzhen.

communication costs to offset the adverse effects of substantial technological disparities. In contrast, cities within the central region tend to exhibit more balanced economic foundations and comparable levels of AI development. This balance in economic and technological conditions reduces the costs of technological alignment, facilitates more efficient resource and technology sharing, and consequently results in the weakest suppressive effect. Similarly, pronounced gaps in economic development and technological capability between northern and southern cities help explain why north–south innovation collaboration is more negatively affected than intra-regional collaboration. In addition, a comparison of intra-regional innovation collaboration across the eastern, central, and western regions reveals that the suppressive effect is strongest within the eastern region. Owing to its early start and rapid progress in AI development, the eastern region has reached a technological frontier, facilitating the sharing of "digital dividends", the establishment of knowledge-sharing platforms, and channels for knowledge spillovers; meanwhile, stronger intellectual property protection accelerates the substitution of traditional innovation collaboration with informal knowledge spillovers.

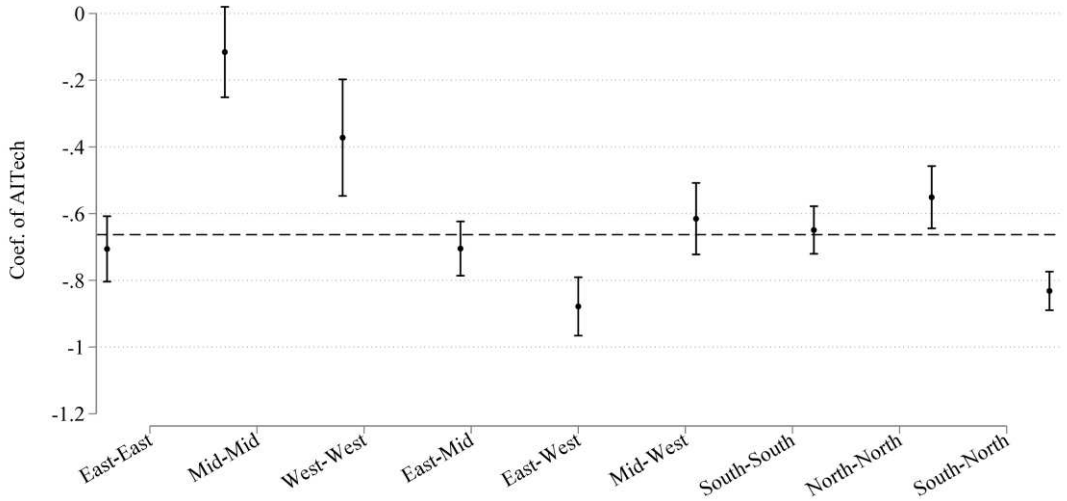


Figure 3. Effects of AI development on innovation collaboration across regions

Finally, Figure 4 illustrates the heterogeneous effects of AI development on collaboration among different types of inventors, including firms, universities, and research institutes. The results indicate that AI development suppresses innovation collaboration across all three actor types, with the strongest inhibitory effect observed in inter-firm collaboration. Competitive relationships between collaboration partners shape their willingness to share knowledge and technologies, thereby affecting both the quantity and quality of collaborative patents. Compared with universities and research institutes, firms face more intense competition, which is further amplified by AI development; to maintain or enhance competitive advantages, firms increasingly deploy AI technologies in managerial and operational activities to create new value and engage in cross-domain competition (Cennamo, 2021). As competition intensifies, collaboration partners become

more cautious in sharing knowledge and technologies and more reluctant to disclose core technologies, potentially undermining innovation quality. By contrast, the nonprofit orientation of universities and research institutes mitigates competitive tensions and promotes knowledge and technology sharing (Azagra-Caro et al., 2017). Consequently, AI development exerts a more pronounced inhibitory effect on innovation collaboration between firms.

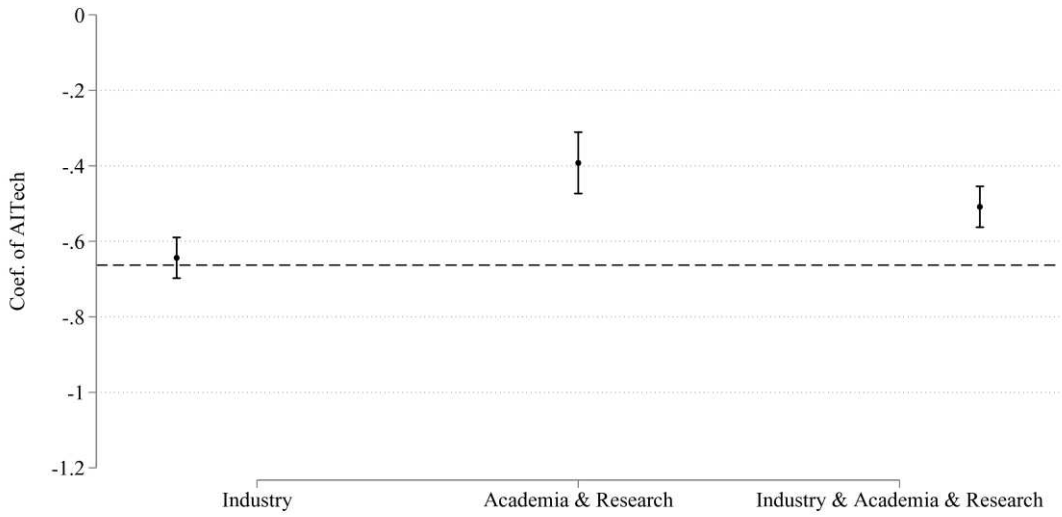


Figure 4. Effects of AI development on collaboration among different types of inventors

4.3. Mechanisms

Theoretical hypotheses suggest that AI development may hinder formal inter-city innovation collaboration by increasing certain collaboration costs and by changing how cities access external knowledge. The following tests are designed to provide theory-guided supportive evidence for these mechanisms, rather than definitive identification of separate causal channels. This distinction matters because collaboration costs, knowledge spillovers, and formal joint innovation may interact in several ways. Improved knowledge access can sometimes support better partner matching and higher-quality collaboration, but it can also produce a substitution effect when cities can obtain useful external knowledge through less formal channels and therefore rely less on formal joint patenting. Therefore, this section examines whether the empirical patterns are consistent with two related explanations: a cost channel, in which AI-related specialization and uneven capability development make formal collaboration more difficult; and a substitution channel, in which expanded knowledge access weakens the marginal need for formal inter-city collaboration.

4.3.1. Innovation Collaboration Costs

AI development may intensify urban specialization and centralization, increase the costs of inter-city innovation collaboration and consequently hinder such collaboration. Building on the above analysis, this study computes three indicators: technological similarity between cities

($tech_similarity$), similarity in AI development levels ($ai_similarity$), and similarity in infrastructure development levels ($infra_similarity$). Interaction terms with the core dependent variable $AITech$ are created, and regressions are conducted using a moderation effect model.

To measure inter-city technological similarity ($tech_similarity$), this study first extracts the distribution of IPC main classes from each city's annual patent applications and constructs a technological composition vector for each city. Then, for each city pair, the cosine similarity between their technological composition vectors is calculated. This indicator ranges from 0 to 1, with higher values reflecting greater technological similarity between cities and lower levels of urban specialization.

The calculation formulas for inter-city AI development similarity ($ai_similarity$) and inter-city infrastructure development similarity ($infra_similarity$) are as follows:

$$X_{similarity_{ij}} = \frac{x_i + x_j - |x_i - x_j|}{x_i + x_j + |x_i - x_j|} \quad (2)$$

In this context, i and j represent the cities in a pair, and X denotes ai or $infra$, reflecting each city's level of AI and infrastructure development. AI development is measured in the same way as in the baseline regression, while infrastructure development is proxied by the area of urban road construction. This indicator ranges from 0 to 1, with higher values reflecting greater similarity between cities in AI and infrastructure development and lower levels of centralization.

Table 8 shows that the coefficient of $AITech \times tech_similarity$ is significantly positive, suggesting that in cities with high technological similarity (i.e., low regional specialization), the negative effect of AI development on inter-city innovation collaboration is substantially mitigated. We interpret this result as consistent with the argument that technological proximity may reduce matching frictions, communication difficulties, and absorptive barriers in cross-city collaboration. The coefficient of $AITech \times ai_similarity$ is also significantly positive, indicating that when two cities have more comparable AI development levels, the negative association between AI development and collaboration is attenuated. This pattern is consistent with the view that balanced AI capabilities reduce capability gaps and information uncertainty between potential partners.

Similarly, The coefficient of $AITech \times infra_similarity$ is also significantly positive, suggesting that in regions with comparable infrastructure levels, the negative effect of AI development on innovation collaboration is substantially alleviated. This finding underscores the importance of balanced infrastructure development in lowering collaboration costs. Comparable infrastructure levels reduce costs associated with technical compatibility and standardization, enhance collaboration efficiency, and their positive moderating effect alleviates the negative impact of AI development on innovation collaboration. Taken together, these results provide evidence consistent with the cost-channel interpretation of Hypothesis 1: similarity in technological bases, AI capabilities, and infrastructure conditions appears to moderate the relationship between AI development and inter-city collaboration by improving the conditions under which cities can communicate, match capabilities, and absorb external knowledge. However, these variables should

be understood as indirect proxies for collaboration-cost conditions rather than as direct measures of coordination costs, transaction costs, or information asymmetries[1].

Table 8. Regression results of the effect of AI development on collaboration costs

	Regional specialization	Regional centralization	
	(1)	(2)	(3)
AITech	-0.914***	-0.071***	-0.069***
	(0.031)	(0.003)	(0.003)
AITech×tech_similarity	0.634***		
	(0.040)		
tech_similarity	-4.037***		
	(0.339)		
AITech×ai_similarity		0.012***	
		(0.003)	
ai_similarity		-0.094***	
		(0.025)	
AITech×infra_similarity			0.017***
			(0.004)
infra_similarity			-0.125***
			(0.029)
Control	Y	Y	Y
City FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	47677	47677	23614
Adjusted R^2	0.40	0.66	0.67

4.3.2. Substitution of Innovation Collaboration

Based on the previous theoretical analysis, AI development may produce a substitution effect by changing the relative value of external knowledge access and formal inter-city collaboration. This does not imply that stronger knowledge spillovers necessarily reduce formal collaboration. Knowledge spillovers may also generate scale or matching effects that facilitate collaboration. Our purpose here is narrower: to examine whether the observed knowledge-flow patterns are consistent with the possibility that expanded access to external knowledge reduces cities' reliance on formal joint patenting in some contexts. To examine this possible mechanism, different dependent variables are employed, as reported in columns (1)--(3) of Table 9. Knowledge learning is proxied by the logarithm of the total citations each city's patents make to patents in other cities during the current year. Knowledge diffusion is measured as the logarithm of the total citations of a city's patents by other cities over the preceding three years. Spillover boundaries are captured using the province-level knowledge spillover localization index from Singh and Marx (2013). All variables are

[1] Directly observing inventor-level coordination costs, transaction costs, or information asymmetries is not feasible with the city-pair patent panel used in this study. The similarity variables are therefore used to capture empirically observable conditions that are theoretically related to collaboration costs. The results should be interpreted as consistency evidence for the cost-channel mechanism, not as a direct measurement of collaboration costs.

aggregated at the province-pair level.

The results in columns (1)–(3) of Table 9 provide important evidence from a knowledge-flow perspective and are broadly consistent with the substitution-effect mechanism. Columns (1) and (2) show that AI development is associated with stronger inter-city knowledge learning and diffusion. Column (3) indicates that knowledge spillovers become less localized and less constrained by provincial boundaries. These patterns suggest that AI expands the channels through which cities access external knowledge. In combination with the baseline decline in joint patent collaboration, they support the interpretation that cities may rely less on formal joint patenting when AI improves access to external knowledge through less formal channels[1].

At the same time, we interpret this evidence with appropriate caution. Expanded knowledge flows can have more than one implication: they may facilitate formal collaboration by improving partner search, or they may reduce reliance on formal collaboration when cities can acquire and recombine external knowledge without establishing formal joint patenting arrangements. For this reason, Table 9 should be read together with the baseline results and the heterogeneity analysis rather than as a standalone proof of substitution. The full set of results is consistent with a substitution effect, while we avoid claiming that the channel has been separately and conclusively identified.

The subsample results based on the patent insurance pilot provide additional support for this interpretation. In cities and periods with stronger patent protection, AI development is associated with a larger decline in formal innovation collaboration. This pattern is consistent with the idea that institutional constraints and knowledge-protection concerns increase the relative cost of formal collaboration, making external knowledge access through less formal channels more attractive. Overall, the mechanism results indicate that AI development is associated with both changes in knowledge-flow conditions and heterogeneity in formal collaboration costs, which together help explain why formal inter-city innovation collaboration declines more strongly in some contexts than in others.

Table 9. Regression results of the effect of AI development on knowledge-flow channels and formal collaboration

	(1)	(2)	(3)	(4)	(5)
	Knowledge learning	Knowledge diffusion	Spillover localization	Pilot cities with patent protection	Non-pilot cities for patent protection
AITech	0.740***	0.800***	-0.153***	-1.230***	-0.651***
	(0.004)	(0.004)	(0.059)	(0.108)	(0.021)
Control	Y	Y	Y	Y	Y

[1] At the same time, we interpret this evidence with appropriate caution. Expanded knowledge flows can have more than one implication: they may facilitate formal collaboration by improving partner search, or they may reduce reliance on formal collaboration when cities can acquire and recombine external knowledge without establishing formal joint patenting arrangements. For this reason, Table 9 should be read together with the baseline results and the heterogeneity analysis rather than as a standalone proof of substitution. The full set of results is consistent with a substitution effect, while we avoid claiming that the channel has been separately and conclusively identified.

City FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	41080	29543	7922	4420	43214
Adjusted R^2	0.98	0.98	0.66	0.48	0.38

5. Conclusion and discussion

This paper examines how artificial intelligence development is associated with formal patent-based inter-city innovation collaboration using patent data from 284 Chinese cities over the period 2010-2022. After addressing potential endogeneity concerns, the analysis shows that AI development is associated with weaker formal joint-patenting collaboration between cities, suggesting a reconfiguration of the balance between autonomous innovation and inter-city collaboration. Contrary to the expectation that AI reduces search costs and facilitates knowledge matching, the net association in the patent-based collaboration network is inhibitory rather than facilitative. This finding does not imply that AI reduces all forms of collaboration. Rather, it suggests that AI development may weaken formal, legally recorded collaboration ties even as other channels of knowledge access and digital interaction become more available.

The suppressive effect operates through two distinct channels. The cost channel reflects how AI development intensifies urban specialization and centralization. As cities deepen their AI capabilities along divergent technological trajectories, cognitive distances widen and coordination costs rise. The concentration of AI resources in hub cities further amplifies information asymmetries and capability-matching frictions. The substitution channel captures how AI-enhanced knowledge spillovers enable cities to access external technological knowledge through informal means—patent mining, intelligent literature search, and cross-boundary learning—thereby crowding out formal collaboration arrangements. Together, these mechanisms reshape inter-city knowledge flows in ways that favor autonomous innovation over partnership formation.

Further analysis demonstrates that the inhibitory effect varies across collaboration types and spatial configurations. High-quality collaborations involving invention patents are more severely affected than those centered on utility models, reflecting how widening regional technological disparities constrain access to frontier innovation partnerships. Cross-provincial collaborations experience stronger suppression than within-province partnerships, as geographic and administrative distance compounds coordination costs. Among regions, eastern cities—where AI development is most advanced and intellectual property protection most stringent—exhibit the most pronounced suppressive effects, while collaborations spanning eastern and western regions face the greatest inhibition. The dampening effect also proves strongest for inter-firm collaboration, where competitive pressures intensify reluctance to share core technologies.

These findings carry more specific policy implications for China's regional innovation system. This reconfiguration cautions against viewing AI development through a purely technology-centric lens. Because the inhibitory effect is stronger for cross-provincial partnerships, policy responses

should focus first on the institutional frictions that make inter-city collaboration costly across administrative boundaries. This does not imply that governments should simply create more knowledge-sharing platforms. Rather, such platforms need to be connected to clearer cross-regional arrangements for joint patent applications, patent ownership, technology licensing, benefit sharing, data access, and dispute resolution in collaborative invention. In this sense, streamlined intellectual property arrangements refer not to weaker protection, but to more predictable, lower-cost, and geographically accessible procedures for coordinating rights and responsibilities in cross-regional innovation projects.

The heterogeneity results further suggest that policy should be differentiated across regions and collaboration types. The stronger inhibitory effect in eastern cities and inter-firm collaborations indicates that AI may amplify the strategic value of proprietary knowledge and increase reluctance to engage in formal partnerships. Policy design should therefore avoid treating collaboration as an objective in itself and should instead reduce the transaction, cooperation, and knowledge-management costs that make collaborative innovation less attractive when AI expands informal access to external knowledge. For central and western cities, the priority is to strengthen absorptive capacity through digital infrastructure, technical talent development, sustained R&D investment, and institutional support for applying external knowledge, so that AI-driven specialization and centralization do not further weaken their participation in high-quality innovation networks.

This study has limitations that point toward future research. Most importantly, the dependent variable captures formal patent-based collaboration and cannot directly observe non-patent forms of collaboration, including open-source communities, model-sharing platforms, algorithm competitions, remote development, contract research, consulting, and informal knowledge exchange. These forms of collaboration are increasingly relevant in the AI era and may evolve differently from joint patenting. Future research could combine patent data with platform-based collaboration records, software repository data, or survey evidence to examine whether AI substitutes for formal collaboration, redirects collaboration toward non-patent channels, or affects different collaboration modes in heterogeneous ways. The present findings should therefore be interpreted as evidence on formal joint-patenting collaboration rather than on the full universe of inter-city technological collaboration.

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