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Economic Impact of University Knowledge Spillovers on Firm Innovation: A Spatial Analysis from China

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ABSTRACT

University knowledge spillovers are widely recognized as vital drivers of corporate innovation and regional economic development. However, the economic impact of geographic distance between enterprises and universities on innovation output remains underexplored. This study investigates the relationship between spatial proximity to universities and corporate innovation performance using invention patent data from Chinese A-share listed firms between 2010 and 2022. Employing Ordinary Least Squares (OLS) models with city and year fixed effects, we find a significant negative association between geographic distance and firms' innovation outputs. Mechanism analyses identify university–enterprise patent collaboration and firms' innovation-related information disclosure as key economic channels for knowledge spillover effects. Moreover, heterogeneity analyses show that these effects are more pronounced in cities with smaller economic scales or limited innovation resources, underscoring the importance of spatial economic factors. By analyzing the impact of university knowledge spillovers on firm innovation, this study broadens the set of identified determinants of corporate innovation, thereby providing additional evidence and theoretical foundations for advancing high-quality, innovation-driven economic development.

1. Introduction

1.1 Motivation for Conducting Research

Technological innovation is widely recognized as a critical driver of economic growth [1]. In recent years, China has actively pursued an innovation-driven strategy, transitioning its economic growth model from reliance on factor inputs and investment toward innovation-led, high-quality development. Within this transformation, universities and enterprises have emerged as pivotal actors in fostering innovation. Universities play a vital role in China's knowledge innovation system. The 'Double First-Class' initiative, launched by the State Council in 2015, significantly bolstered the resources and prestige of China's leading universities. This policy has elevated the standing of these

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universities domestically, improving their attractiveness to both students and faculty. Consequently, these institutions can mobilize increased financial resources and recruit high-caliber researchers. Simultaneously, governmental policy has actively encouraged stronger integration among industry, academia, and research institutions to convert university-generated technologies into practical productivity gains [2]. Furthermore, the “Outline of the National Innovation-driven Development Strategy” issued by the State Council in 2016, established innovation as a national strategic priority, thereby accelerating the commercialization and industrial application of scientific research and enabling technological innovation to more effectively stimulate enterprise growth.

Universities and enterprises exhibit distinct emphasis on technological innovation. Universities primarily conduct scientific research and foundational innovation, aiming to produce scientific knowledge and develop skilled talent without direct profit-driven motives. In China, where most universities are government-funded, higher education institutions spent RMB 275.33 billion on research and development (R&D) in 2023, accounting for 8.3% of the national total R&D investment, according to the 2023 Statistical Bulletin on China's Science and Technology Expenditures. Such research activities often yield public goods characterized by non-rivalry and non-excludability, particularly evident in openly disseminated outputs such as journal articles and academic presentations, which become universally accessible [3,4]. Nevertheless, patents and proprietary technologies may impose limitations on non-excludability. These non-rivalrous and partially non-excludable characteristics facilitate positive externalities through knowledge spillovers from universities to broader societal entities [5]. Universities prioritize long-term academic value and cumulative knowledge generation, thereby laying the groundwork for future technological advancements, even when their scientific outputs lack immediate industrial applicability.

In contrast, enterprises focus primarily on applied research and technology commercialization, driven fundamentally by profit objectives. Consequently, enterprise-led innovation tends to be demand-driven, prioritizing efficiency and immediate economic returns. Belderbos *et al.,* [7] found that firms often prioritize innovation projects that deliver rapid market benefits. Firms selectively invest in research projects anticipated to yield prompt economic benefits. This complementarity enables universities to consistently generate novel concepts, technologies, and highly skilled personnel, which enterprises subsequently adapt and commercialize into marketable products or innovative processes. Thus, the interaction between universities and enterprises establishes an integrated pathway from knowledge creation to commercial application, fostering a beneficial synergy between fundamental research and industrial innovation [2]. The inherent differences—university knowledge being fundamentally public, non-profit, and oriented toward long-term accumulation, versus enterprise innovation being market-oriented and application-focused—highlight the importance of knowledge transfer between these two entities, a process significantly influenced by geographic proximity [5].

Knowledge dissemination, especially of tacit knowledge, frequently requires interpersonal interaction and face-to-face communication to be effective [6]. Consequently, knowledge spillovers are inherently subject to geographic limitations, with proximity significantly enhancing their effectiveness [8]. Thus, even universities possessing substantial technological innovation capabilities may not fully realize their spillover potential due to geographic constraints. This underscores the importance of geographic proximity in knowledge diffusion and collaborative innovation. Furthermore, it provides strategic insights into government policies supporting enterprises, suggesting, for instance, the establishment of technology parks or industrial clusters strategically located near universities to optimize spatial alignment. Zhong and Li [8] discuss how governments worldwide have established various university-based innovation parks to promote university-enterprise collaboration. For example, the UK's 2014 'University Enterprise Zones' pilot aimed to foster university-industry cooperation in designated regions. In the United States, Cambridge City planned an innovation district near MIT in 2012. More recently, cities like Shanghai and Hangzhou in China have developed 'innovation corridors' around their universities. Consequently, analyzing university-enterprise interactions from a geographic and spatial perspective is crucially important.

While prior studies have made significant progress in understanding university knowledge spillovers, important questions remain regarding how geographic distance affects enterprise innovation. These issues are further discussed in the Section 2 Literature Review. Although a substantial body of literature has examined university knowledge spillovers, most prior studies have focused on macro-level indicators, such as regional patent counts or aggregate economic performance, while firm-level perspectives have received comparatively limited attention. There remains a need for research that employs comprehensive firm-level data across Chinese regions to provide systematic quantification. Addressing this gap can assist firms in formulating strategies to enhance innovation output and enable governments to better leverage local universities in promoting regional economic and innovation development. Accordingly, the purpose of this study is to empirically investigate the impact of geographic distance between universities and firms on firms' innovative performance.

1.2 Practical and Methodological Aims of the Study

This study investigates how geographic distance between universities and enterprises influences enterprises' innovation output. Using annual counts of invention patents obtained by China's A-share listed companies to measure their innovation output, geographic distances are computed based on latitude and longitude coordinates of both enterprises and universities. Patent counts are widely recognized and employed as valid indicators of innovation outcomes in empirical research [9]. Patent data for the listed companies are sourced from the State Intellectual Property Office's patent database. Information on university locations and attributes is obtained from publicly available Ministry of Education datasets, while enterprise coordinates and financial data are collected from databases such as China Stock Market and Accounting Research (CSMAR).

Methodologically, the study employs multiple regression models combined with fixed-effects models, rigorously controlling for confounding variables that may influence the relationship between geographic distance and innovation output, a robust empirical approach commonly applied in knowledge spillover research [10]. Additionally, subgroup analyses, robustness checks, mechanism explorations, and heterogeneity analyses are conducted to reinforce the reliability and validity of the findings. The empirical results reveal a significant negative relationship between geographic distance and enterprise innovation output, indicating that closer proximity substantially enhances innovation productivity. This effect is especially pronounced among enterprises located in less-developed regions.

1.3 Contributions of the Study

Academically, this study advances existing literature by empirically examining the mechanisms through which spatial geographic factors affect knowledge spillovers at the micro-level, thereby enriching the empirical evidence for spatial knowledge spillover theory. From a practical standpoint, the findings offer actionable insights for enterprises considering the optimal locations for R&D centers or offices near universities, facilitating improved utilization of academic knowledge spillovers. Moreover, the study suggests policy recommendations for regions with limited educational resources, such as developing industrial parks near existing universities and encouraging external universities to establish local branches. Overall, this research addresses critical gaps in understanding the impact of geographic proximity between universities and enterprises on innovation output, providing valuable guidance for optimizing governmental policies and enhancing collaborative innovation between academic and industry.

1.4 Organization of the Paper

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on the impact of geographic distance between universities and enterprises on enterprises or the factors affecting firm innovation. Section 3 develops the theoretical framework and research hypotheses. Section 4 describes the data sources, variable construction, and empirical methodology. Section 5 presents empirical findings, including robustness checks, mechanism analyses, and heterogeneity analyses. Section 6 concludes with a summary of the study, highlighting its contributions, policy implications, and directions for future research.

2. Literature Review

The influence of universities on firms manifests across multiple dimensions, including financing, governance, and market valuation. Lin [3] demonstrates that firms located near research universities experience reduced financing constraints and enhanced capital market performance, thereby creating favorable conditions for R&D investment. Qiu *et al.,* [2] argue that close collaboration between universities and firms strengthens corporate governance by encouraging managers to adopt a long-term, innovation-oriented perspective. Moreover, firms in close proximity to universities generally achieve higher market valuations and exhibit greater growth potential [3]. Taken together, these findings indicate that the impact of universities on firms is strongly shaped by geographic proximity. Beyond these channels, knowledge spillovers that promote corporate innovation are also deeply influenced by geographic distance.

Numerous studies confirm these spatial constraints, illustrating that the impact of innovative knowledge diminishes as geographic distance increases [11, 12]. Enterprises situated closer to universities can more readily form industry-academia networks through academic seminars and personnel exchanges, facilitating smoother knowledge spillovers. As Mowery and Ziedonis [13] propose in their theoretical model, shorter distances reduce informational and transactional costs associated with acquiring research outcomes, thereby accelerating the transfer of university technologies. Conversely, firms located further away face higher costs and delays in accessing cutting-edge university research and technological services, demonstrating that geographic distance significantly hampers enterprise absorption of university-generated knowledge [14].

Universities are not the sole determinants of firms' innovation outcomes. In addition to the spatial effects generated by knowledge spillovers, both internal firm characteristics and external environmental conditions substantially influence innovation output. Internally, climate risk disclosures enhance firms' innovation capacity by strengthening reputational capital, improving governance, and reducing financing costs [15]. Zhang *et al.,* [16] emphasize the dual role of corporate culture: innovation cultures driven by management may increase patent quantity at the expense of quality, whereas cultures embraced by employees can simultaneously enhance both. Likewise, demonstrate that digital infrastructure improves R&D efficiency and overall innovation outcomes. the expansion of digital finance alleviates financing constraints and significantly promotes breakthrough innovation [12]. Externally, Belderbos *et al.,* [7] underscore the importance of sustained external collaborations in driving innovation performance. Nevertheless, among these multifaceted factors, the role of university knowledge spillovers is distinctive, as their effects are fundamentally conditioned by geographic proximity. Accordingly, examining the geographic distance between universities and firms provides a more comprehensive understanding of the determinants of corporate innovation—a perspective that constitutes the central focus of this study.

Numerous studies have examined the relationship between university knowledge spillovers and the innovation outcomes of nearby enterprises. Audretsch and Lehmann [17], analyzing the German context, validated the theory of knowledge spillover entrepreneurship, showing that regions with higher levels of university-generated knowledge typically experience increased formation of high-tech startups. This occurs because academic knowledge diffuses into entrepreneurial activities, thereby enhancing firms' innovative capabilities in the region. However, earlier research largely adopted macro-level analyses, focusing on the aggregate relationship between universities and regional economic growth or industrial innovation at provincial or regional scales. Such studies typically utilized broad indicators, including regional patent output and overall economic performance [18]. Although effective in demonstrating universities' general impact on regional innovation, these studies fail to adequately capture the heterogeneity in interactions between universities and individual firms. Moreover, the spatial geographic dimension—specifically, the precise geographic distance between universities and enterprises—has received limited attention. Most existing literature employs indicators such as university numbers, research funding, and frequency of academia-industry collaborations to approximate spillover intensity without explicitly accounting for geographic proximity. Furthermore, empirical investigations that quantitatively examine the relationship between geographic distance and innovation outputs at the firm level, utilizing comprehensive nationwide enterprise-level data, remain relatively rare.

3. Theoretical Analysis and Research Hypothesis

In economics, particularly spatial economics, geographic distance is widely acknowledged as a critical factor. Extensive research has identified linear relationships between geographic distance and various economic outcomes. For instance, Agarwal and Hauswald [19] demonstrate that increased geographic distance significantly elevates the cost for stakeholders to access firm-specific information, thereby exacerbating information asymmetry. Similarly, Kubick and Lockhart [20] find that greater distances between regulators and enterprises increase regulatory costs and reduce the efficacy of external monitoring. Conversely, geographic proximity fosters trust and facilitates social networks among enterprises and their partners, enhancing mutual trust and expediting information exchange [21]. Given these considerations, this study posits that geographic proximity between universities and enterprises substantially influences enterprise innovation output. Building on the complementary roles of universities and enterprises, geographic proximity emerges as a crucial factor in facilitating knowledge spillovers.

Geographic proximity serves as an essential condition for effective communication and collaboration between universities and enterprises. Technological innovations generated by universities often require extensive and frequent interactions with enterprises due to their typically early-stage commercial viability, necessitating robust knowledge transfer processes [22]. Geographic proximity minimizes communication costs and facilitates smoother interactions, encompassing both formal academia-industry collaborations and informal exchanges such as academic conferences, talent mobility, and social networking activities [23]. Existing studies, including university relocation experiments in China, have shown that geographic proximity significantly enhances knowledge interaction between universities and nearby enterprises. This effect is particularly pronounced when a larger number of enterprises are located around newly established university campuses [8]. Therefore, closer geographic proximity between universities and enterprises significantly enhances the likelihood of establishing sustained and efficient collaborative relationships, promoting effective knowledge transfer and enhancing enterprise innovation. Frequent interactions and efficient communication resulting from geographic proximity provide a crucial foundation for the knowledge spillover effect of universities.

Knowledge spillovers occur when newly generated university knowledge is disseminated to other entities, such as enterprises, without formal market transactions, typically via personnel exchanges, collaborative research and development (R&D), and face-to-face communication [24]. Frequent and close interactions between academia and industry are crucial to ensuring effective spillovers, especially for transferring tacit knowledge, whose dissemination largely depends on direct interactions and trust built through sustained collaboration. Certain types of knowledge, including researchers' experiential insights and laboratory skills, are challenging to document or communicate via manuals; therefore, face-to-face interactions significantly enhance their diffusion [25]. Additionally, the cost of face-to-face communication declines as geographic distance decreases, and the spillover effect intensifies with prolonged collaboration [7]. Enterprises geographically proximate to universities gain rapid and comprehensive access to cutting-edge academic research, technological trends, and skilled personnel, thereby amplifying the knowledge spillover effect. Thus, the geographic distance between enterprises and universities emerges as a significant external factor influencing corporate innovation output, warranting further in-depth research and empirical investigation.

Previous research highlights several determinants of enterprise innovation outputs, including internal governance structures and financial conditions [26], as well as board composition and structure [27]. Among these, knowledge spillover from universities emerges as a critical external determinant, significantly enhancing enterprise innovation capabilities. University-generated technological innovations often involve advanced, foundational research that equips enterprises with essential insights to resolve technological bottlenecks and pursue innovative development trajectories. University research typically targets emerging, cutting-edge technologies, providing enterprises with novel perspectives and inspiration for technological innovation, thereby enabling more precise identification of viable technological pathways and strategies [25]. Moreover, university knowledge often represents the highest standards in respective fields, characterized by substantial novelty. Accessing such knowledge empowers enterprises to produce more original and competitive innovations, improving the quantity and quality of patent outputs [6]. Regular interactions between universities and enterprises also enable enterprises to remain current with emerging technological trends, facilitating quicker adoption of innovative solutions and higher-quality innovations [28].

Empirical studies consistently support the positive relationship between knowledge spillovers and enterprise innovation. Rodríguez-Gulías *et al.,* [29], for instance, confirmed the critical role of university-level spillovers in fostering the growth and development of university spin-offs in Spain. Similarly, high-tech startups located near universities demonstrate distinct advantages attributable to proximity compared to other types of enterprises, a relationship also validated in emerging economies [26]. Consequently, enterprises can effectively integrate university-generated knowledge into their innovation processes, enhancing their technological leadership and overall innovative performance.

In summary, geographic proximity significantly enhances communication and collaboration between enterprises and universities, thus facilitating the spillover of university-generated knowledge and technological innovations. Enterprises located near universities can more effectively absorb and integrate such knowledge into their innovative activities, resulting in higher innovation outputs.

Building on the theoretical framework and insights from the literature, this study proposes the following three research hypotheses. The first hypothesis is as follows:

Hypothesis 1: Enterprises located closer to universities exhibit higher innovation outputs compared to those situated further away. Specifically, a significant negative correlation exists between geographic distance from universities and enterprise innovation outputs.

As previously discussed, enterprises geographically proximate to universities are more likely to engage in academia-industry collaborative research. Geographic proximity reduces the spatial costs associated with collaborative R&D, enabling frequent face-to-face knowledge exchanges, thereby mitigating misunderstandings and friction in technological diffusion [30]. Shorter distances also enable enterprises to quickly communicate market demands, allowing universities to provide timely theoretical and technical support. Such frequent and efficient exchanges facilitate clearly defined and aligned R&D objectives, improving the quality of patents generated through university-industry collaborations [31]. Additionally, research parks adjacent to universities leverage proximity advantages to provide convenient platforms and intermediary services, significantly increasing the willingness of both enterprises and universities to share critical technologies and core knowledge. This collaborative environment enhances both the efficiency and quality of patent outputs resulting from university-industry cooperation [30].

Thus, this study presents the second hypothesis:

Hypothesis 2: Enterprises located closer to universities will produce more patents through university-industry collaboration, thereby achieving higher overall innovation outputs.

As previously noted, geographical proximity to universities provides enterprises with enhanced opportunities for collaboration and access to innovation resources, thereby elevating their innovation expectations [2]. Enterprises seeking to increase their market value must effectively communicate positive signals to external investors. Innovation activities signal sustained profitability and growth potential, constituting information that firms proactively disclose. Such proactive disclosure typically manifests through a higher frequency of innovation-related keywords in corporate annual reports. Bellstam *et al.,* [32] demonstrate that the frequent use of innovation-related terminology in publicly disclosed documents, such as annual reports, positively influences market perceptions of an enterprise's innovative capacity, thereby transmitting favorable signals to investors.

To mitigate stock price declines from unmet investor expectations, firms may bolster R&D investments or refine related innovation management systems. Critically, these investments target tangible patent outcomes; positive market reactions occur predominantly when innovative efforts yield clear and beneficial results that advance business growth, subsequently enhancing stock valuations. Bellstam *et al.,* [32], employing text-based analytical methods using an "innovation orientation" metric, find that enterprises possessing greater numbers and higher quality of patents consistently incorporate more innovation-related terms in their annual disclosures. More recently, Feng *et al.,* [15] and Gounopoulos *et al.,* [33] demonstrate that textual disclosure characteristics can significantly influence corporate innovation outputs. This perspective is corroborated by Zhang *et al.,* [16], who highlight that executive communications emphasizing innovation priorities typically align with heightened innovation expectations, creating internal pressures that stimulate increased innovation outputs.

Consequently, this study formulates the third hypothesis:

Hypothesis 3: Enterprises geographically proximate to universities exhibit heightened expectations for technological innovation, proactively communicate this information to external investors, and thus experience increased innovation outputs.

4. Methodology

4.1 Sample and Data

This study examines a sample of Chinese A-share listed companies from 2010 to 2022. The selection of the study's period is based on two key reasons: First, patent data for enterprises has been more comprehensively recorded on official websites since 2010, offering a more accurate reflection of the innovation output levels of Chinese enterprises. Second, at the time of data collection, patent data for 2023 and subsequent years had not yet been fully updated, leading to significant gaps that could introduce bias into the study's conclusions.

The use of Chinese A-share listed companies as the research sample is due to their generally more standardized information disclosure systems, which provide comprehensive and verifiable patent data. Furthermore, as a key segment of Chinese enterprises, A-share listed companies serve as a representative sample of the overall innovation status and characteristics of Chinese enterprises.

The dataset integrates information from multiple sources: firm-level data are primarily derived from CSMAR and Chinese Research Data Services (CNRDS) databases; enterprise-level innovation data are sourced from the official website of the State Intellectual Property Office; university-related information is gathered from China Education Online; and city-level data are obtained from the National Bureau of Statistics and the CSMAR database. To ensure reliability and consistency, the initial dataset undergoes the following preprocessing steps: (1) financial sector firms, including banks, insurance companies, and companies marked as ST or *ST during the study period, are excluded to avoid distortions from atypical operational conditions. In the Chinese stock market, "ST" stands for "Special Treatment," a designation used when a listed company's financial or operational conditions become abnormal, signaling potential risks to investors. If the company is at risk of mandatory delisting, it is marked as "*ST."; (2) observations with missing values for critical variables are removed; and (3) continuous variables are winsorized at the 1% and 99% quantiles to mitigate the impact of extreme values. The final sample consists of 31,097 observations from A-share listed companies spanning 2010 to 2022.

4.2 Model Specification and Variable Selection

To investigate how geographic distance between enterprises and universities affects corporate innovation output, the following regression model is specified, following prior studies that incorporate geographic proximity into knowledge spillover analyses [8].

$$Patent_{i,t} = \alpha + \beta Distance_{i,t} + \gamma Controls + \mu_m + \lambda_t + \epsilon_{i,t} \tag{1}$$

In this model, i denotes enterprises, t indicates the year, and m represents the city in which an enterprise is located. The dependent variable $Patent_{i,t}$ measures the level of enterprise innovation output. The explanatory variable $Distance_{i,t}$ captures the geographic distance between an enterprise and its nearest university. Control variables $Controls$ include both firm-specific characteristics and city-level factors. μ_m and λ_t represent city and year fixed effects, respectively, and $\epsilon_{i,t}$ is the random error term. Ordinary Least Squares (OLS) regression is employed with city and year fixed effects included.

The definitions and details of primary variables are summarized in Table 1 below.

This study selects the number of invention patents as the primary indicator for measuring corporate innovation output. The rationale for this choice lies in the fact that, according to the Patent Law of the People's Republic of China, invention patents—defined as new technical solutions proposed for a product, method, or its improvement—involve higher technological content and innovation levels compared to other patent types. For instance, design patents refer to novel aesthetic designs suitable for industrial applications, including the entire or partial shape, pattern, or their combination, as well as combinations of color with shape and pattern. Utility model patents, on the other hand, refer to novel technical solutions concerning the shape, structure, or their combination in a product, designed for practical utility. Consequently, invention patents are generally more representative of the true innovation output of enterprises.

The innovation-related keywords specifically include R&D, patent, innovation, creation, invention, utility model, experiment, process, development, technology, new business, new product, new project, intellectual property, manufacturing, research and development (R&D), research, scientific achievements, science and technology investment, scientific research, design, testing, capitalization, software, and preliminary research.

Table 1
Main Variables and Definitions

Category	Variable Symbol	Variable Definition
Dependent Variable	Patent	The natural logarithm of invention patent counts
	Patent1	The natural logarithm of total patent counts
	Patent2	The natural logarithm of appearance design patent counts
	Patent3	The natural logarithm of utility model patent counts
Explanatory Variable	Distance	The natural logarithm of geographic distance between firm and nearest university
Mechanism Variables	Co_Patent	The natural logarithm of university-enterprise collaboration patents)
	Percentage_Report	Number of innovation-related keywords in annual reports / Total number of keywords in annual reports
Control Variables	Size	Firm size = The natural logarithm of total assets
	LEV	Leverage ratio = Total liabilities / total assets
	Growth	Annual growth rate of total assets
	CapEx	Capital Expenditures = Cash payments for fixed, intangible, and other long-term assets / total assets
	PPE	Property, Plant, and Equipment = Total fixed assets / total assets
	Indep	Number of independent directors / total number of directors
	GDP	The natural logarithm of city Gross Domestic Product (GDP)
	Population	The natural logarithm of city population
	Edu_ratio	City education expenditure / city fiscal expenditure

5. Results

5.1 Descriptive Statistics Analysis

Table 2 summarizes the descriptive statistics for the key variables used in the analysis. The dependent variable, Patent (measured as the natural logarithm of the number of invention patents plus one), exhibits considerable variability, with a minimum value of 0.000, a maximum of 8.899, a mean of 1.057, and a standard deviation of 1.346. This substantial heterogeneity suggests pronounced differences in innovation capabilities across the sample enterprises, characterized by a notably right-skewed distribution. Such variability reflects the diverse industry composition within the sample, where a limited number of firms exhibit strong innovation performance, whereas the majority have relatively few or no patents. Median values for design patents (Patent2) and utility model patents (Patent3) are both zero, further supporting the skewed distribution and infrequency of patent production among most sampled firms.

The primary explanatory variable, Distance (calculated as the natural logarithm of geographic distance between enterprises and their nearest university plus one), has a mean value of 2.092, a median of 1.784, a minimum of 0.065, and a maximum of 8.156. These figures indicate substantial variation in proximity to universities, ranging from enterprises located immediately adjacent to universities to those significantly distant from academic institutions. In economic terms, this suggests that spatial and geographic communication costs, along with the costs of acquiring information, have a significant impact on corporate innovation. Enterprises located closer to universities benefit from reduced knowledge acquisition costs.

Control variables also reveal considerable diversity in enterprise financial and governance characteristics. Firm size (Size) displays a standard deviation of 1.379, suggesting substantial heterogeneity. The leverage ratio (LEV) averages 0.434 with a median of 0.424, indicating moderate leverage levels among enterprises. City-level controls, including GDP and Population, similarly demonstrate significant variation, likely influencing enterprise innovation outcomes and underscoring their relevance as controls. This aligns with fundamental economic principles, as enterprises with such proximity are more likely to allocate greater resources toward patent research and development, leading to higher levels of innovation output.

Collectively, these descriptive statistics illustrate marked variability across enterprises regarding innovation activities, geographic proximity to universities, and governance structures. Such variability provides a robust empirical foundation for examining the relationship between geographic distance to universities and enterprise innovation outputs.

Table 2
Descriptive Statistics

Variable Name	Obs	Mean	SD	Min	Median	Max
Patent	31097	1.057	1.346	0.000	0.693	8.899
Patent1	31097	1.482	1.630	0.000	1.099	9.430
Patent2	31097	0.360	0.900	0.000	0.000	6.829
Patent3	31097	0.905	1.330	0.000	0.000	8.395
Distance	31097	2.092	1.401	0.065	1.784	8.156
Co_Patent	31097	0.050	0.284	0.000	0.000	4.394
Percentage_Report	30794	0.032	0.065	0.000	0.004	0.789
Size	31097	22.224	1.379	15.979	22.036	30.370
LEV	31097	0.434	0.215	0.050	0.424	0.979
Growth	31097	0.599	1.621	-17.313	0.377	64.696
CapEx	31097	0.048	0.049	-0.000	0.033	0.642
PPE	31097	0.198	0.160	0.000	0.162	0.971
Indep	31097	0.378	0.057	0.143	0.364	1.000
GDP	31097	9.113	1.072	4.900	9.289	10.707
Population	31097	6.507	0.661	3.171	6.567	8.137
Edu_ratio	31097	0.166	0.034	0.010	0.162	0.423

5.2 Baseline Regression Analysis

This study employs Ordinary Least Squares (OLS) regression analysis using the specified research model to empirically test Hypothesis 1, which examines the impact of geographic distance between enterprises and universities on innovation output. The regression results are presented in Table 3. To clearly identify the influence of explanatory variables, column (1) presents results without control variables, column (2) includes firm-level control variables, and column (3) incorporates all control variables.

In all model specifications, the coefficients for Distance are negative and statistically significant at the 1% level, confirming that increased geographic distance between enterprises and universities significantly reduces enterprise innovation output. This finding aligns with the theoretical predictions of knowledge spillover theory, indicating that greater distances hinder firms' access to university-generated knowledge, consequently diminishing innovation outputs. Conversely, closer geographic proximity facilitates knowledge and technology transfer from universities, thereby enhancing enterprises' innovation activities.

Among the control variables, the coefficient for leverage ratio (LEV) is negative and significant at the 1% level, suggesting that higher debt levels negatively impact innovation performance. Conversely, the coefficients for capital expenditures (CapEx) and firm size (Size) are positive and significant at the 1% level, indicating that firms with greater investment in capital assets and larger size demonstrate higher innovation outputs due to better technological resources and economies of scale.

In summary, the baseline regression analysis provides empirical support for Hypothesis 1, revealing a significant negative relationship between geographic distance from universities and enterprise innovation output.

Table 3
Baseline Regression Results

	(1) Patent	(2) Patent	(3) Patent
Distance	-0.049***	-0.056***	-0.056***
	(-2.701)	(-2.899)	(-2.901)
Growth		-0.003	-0.003
		(-0.559)	(-0.561)
LEV		-0.771***	-0.774***
		(-7.133)	(-7.167)
PPE		-0.227	-0.229
		(-1.547)	(-1.557)
CapEx		2.790***	2.790***
		(5.804)	(5.803)
Size		0.196***	0.197***
		(10.075)	(10.079)
Indep		0.266	0.266
		(0.882)	(0.880)
GDP			-0.002
			(-0.024)
Population			0.211*
			(1.864)
Edu_ratio			-0.553
			(-1.281)
City Fixed Effects (FE)	Y	Y	Y
Year FE	Y	Y	Y
_cons	1.003***	-3.244***	-4.643***
	(39.086)	(-8.215)	(-4.126)
N	31097	31097	31097
R^2	0.112	0.154	0.154

Note: This table reports regression results examining the impact of geographic distance on the number of invention patents held by listed companies from 2010 to 2022. All regression results are adjusted for clustering at the city level. Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

To further assess the robustness of the baseline findings, additional regressions are conducted using alternative dependent variables, including total patents (Patent1), appearance design patents (Patent2), and utility model patents (Patent3). Results from these analyses are presented in Table 4. The findings indicate a lower statistical significance for the variable Distance across these alternative patent categories, aligning with expectations. Specifically, geographic proximity to universities exhibits the strongest positive effect on invention patents, which represent higher technological sophistication, as demonstrated in the baseline results. Conversely, appearance design patents and utility model patents, typically involving lower technological complexity, show weaker dependence on university proximity. Consequently, the aggregate patent count, incorporating all three patent types, demonstrates lower significance compared to invention patents alone.

Table 4
Regression Results for Other Patent Types

	(1) Patent1	(2) Patent2	(3) Patent3
Distance	-0.062**	-0.022*	-0.034*
	(-2.538)	(-1.949)	(-1.899)
Growth	-0.000	-0.005	-0.002
	(-0.003)	(-1.403)	(-0.342)
LEV	-0.932***	-0.309***	-0.338***
	(-8.386)	(-6.284)	(-4.453)
PPE	-0.174	-0.404***	0.023
	(-0.902)	(-5.501)	(0.126)
CapEx	3.068***	0.482**	1.488***
	(5.890)	(2.529)	(3.910)
Size	0.190***	0.080***	0.140***
	(7.841)	(5.773)	(5.717)
Indep	0.449	0.256	0.305
	(1.227)	(1.200)	(1.032)
GDP	-0.079	-0.063	-0.149
	(-0.702)	(-1.217)	(-1.514)
Population	0.325***	0.018	0.146
	(2.615)	(0.307)	(1.331)
Edu_ratio	-0.585	0.123	-0.887*
	(-1.156)	(0.442)	(-1.815)
City FE	Y	Y	Y
Year FE	Y	Y	Y
_cons	-4.293***	-0.984	-1.927
	(-3.079)	(-1.634)	(-1.533)
N	31097	31097	31097
R2	0.172	0.089	0.165

Note: This table reports regression results examining the impact of geographic distance on the total number of patents, design patents, and utility model patents for listed companies from 2010 to 2022. All regression outcomes are adjusted for clustering at the city level, with significance levels of 1%, 5%, and 10% denoted by ***, **, and *, respectively.

5.3 Robustness Checks

To validate the reliability of the findings, multiple robustness checks from different perspectives are performed (Tables 5, 6, and 7). Initially, the data source for the dependent variable is altered by using annual invention patent counts obtained from the CSMAR database, while maintaining consistent data preprocessing procedures. The regression results, presented in Table 5, reinforce the primary conclusions. Although the magnitude of the coefficients slightly decreases relative to baseline regression, which is likely due to variations in patent data coverage between sources—the direction and significance remain consistent, indicating the robustness of the baseline findings across different data sources.

Table 5
Robustness Check 1: CSMAR Invention Patent Counts

	(1) CS_Patent	(2) CS_Patent	(3) CS_Patent
Distance	-0.012***	-0.012***	-0.012***
	(-2.699)	(-2.664)	(-2.628)
Growth		0.008***	0.008***
		(3.841)	(3.825)
LEV		-0.235***	-0.236***
		(-6.156)	(-6.252)
PPE		-0.234***	-0.235***
		(-7.747)	(-7.830)
CapEx		0.956***	0.954***
		(8.187)	(8.176)
Size		-0.004	-0.004
		(-0.784)	(-0.752)
Indep		-0.125	-0.124
		(-1.470)	(-1.462)
GDP			0.077*
			(1.940)
Population			0.074
			(1.234)
Edu_ratio			-0.389
			(-1.624)
City FE	Y	Y	Y
Year FE	Y	Y	Y
_cons	0.162***	0.377***	-0.844*
	(10.186)	(3.209)	(-1.842)
N	31097	31097	31097
R^2	0.033	0.047	0.047

Note: This table presents regression results examining the impact of geographic distance on invention patents, utilizing patent data from the CSMAR database for listed companies during the period 2010–2022. All regressions are adjusted for clustering at the city level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Second, considering the discrete nature of patent data and potential sensitivity arising from logarithmic transformations when zeros are present, a Poisson regression model is employed as an additional robustness check. Chen and Roth [34] emphasize that log transformations can lead to heightened sensitivity to measurement scales in cases with zero-value observations. Results from the Poisson regressions, presented in Table 6, indicate that the coefficient on Distance remains significantly negative, further supporting the robustness of Hypothesis 1.

Third, to account for the potential influence of first-tier cities (Beijing, Shanghai, Guangzhou, and Shenzhen), which exhibit higher concentrations of universities and enterprises, we conduct a robustness check by excluding firms located in these cities and re-estimating the regressions. The results, displayed in Table 7, persistently show a significantly negative relationship between geographic distance and innovation output. This finding indicates that the observed relationship between university-enterprise proximity and innovation outcomes is not driven solely by spatial agglomeration effects in first-tier cities.

Table 6
Robustness Check 2: Poisson Regression Results

	(1) Patent	(2) Patent	(3) Patent
Distance	-0.055***	-0.061***	-0.061***
	(-2.684)	(-2.781)	(-2.777)
Growth		0.001	0.001
		(0.135)	(0.130)
LEV		-0.844***	-0.848***
		(-7.228)	(-7.264)
PPE		-0.232*	-0.233*
		(-1.677)	(-1.679)
CapEx		2.531***	2.531***
		(7.171)	(7.165)
Size		0.189***	0.189***
		(13.222)	(13.232)
Indep		0.176	0.177
		(0.587)	(0.590)
GDP			0.024
			(0.263)
Population			0.228**
			(2.114)
Edu_ratio			-0.712*
			(-1.691)
City FE	Y	Y	Y
Year FE	Y	Y	Y
_cons	-0.017	-4.096***	-5.855***
	(-0.531)	(-13.504)	(-5.189)
N	31097	31097	31097

Note: This table presents Poisson regression results investigating the impact of geographic distance on the number of invention patents held by listed companies from 2010 to 2022. All regressions are adjusted for clustering at the city level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

First-tier cities have relatively abundant research resources, including not only universities but also other research institutions, which can influence corporate innovation. However, robustness checks reveal that the conclusions of the baseline regression are applicable to enterprises in a broader range of ordinary cities.

In summary, the robustness checks consistently reinforce the baseline findings, reliably confirming the negative relationship between geographic distance from universities and enterprise innovation outputs.

Table 7
Robustness Check 3: Excluding First-tier City Samples

	(1) Patent	(2) Patent	(3) Patent
Distance	-0.052***	-0.063***	-0.063***
	(-3.219)	(-3.674)	(-3.681)
Growth		-0.004	-0.004
		(-0.746)	(-0.737)
LEV		-0.652***	-0.655***
		(-5.912)	(-5.946)
PPE		-0.385***	-0.387***
		(-2.955)	(-2.975)
CapEx		1.910***	1.908***
		(6.357)	(6.348)
Size		0.203***	0.204***
		(7.257)	(7.259)
Indep		0.188	0.187
		(0.585)	(0.585)
GDP			-0.011
			(-0.126)
Population			0.392**
			(2.086)
Edu_ratio			-0.500
			(-0.847)
City FE	Y	Y	Y
Year FE	Y	Y	Y
_cons	0.752***	-3.500***	-6.031***
	(18.899)	(-5.638)	(-4.080)
N	21148	21148	21148
R2	0.147	0.182	0.183

Note: This table reports regression results examining the impact of geographic distance on the invention patent counts for listed companies located outside first-tier cities during the period 2010–2022. All regression analyses are adjusted for clustering at the city level. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

5.4 Mechanism Analysis

Universities can facilitate enterprise innovation through multiple channels. To uncover the mechanisms through which geographic distance influences enterprise innovation outcomes, this study investigates two potential pathways: university-enterprise collaboration and disclosure of innovation-related information. If closer proximity to universities increases collaborative patent outputs or encourages enterprises to emphasize innovation activities in their annual reports, these mechanisms may partially mediate the impact of geographic distance on innovation outputs.

Specifically, we regress the number of university-enterprise collaborative patents (Co_Patent) and the proportion of innovation-related keywords in annual reports (Percentage_Report) on geographic distance (Distance) to test these mediating effects.

Table 8 shows that the coefficient for Distance is significantly negative at the 1% level for collaborative university-enterprise patents. This result indicates that enterprises located further from universities generate fewer collaborative patents, suggesting geographic distance negatively affects collaborative innovation efforts between enterprises and universities. Geographic proximity reduces collaboration costs, thereby facilitating joint patent activities and directly enhancing enterprise innovation outputs. Conversely, enterprises located farther from universities face greater barriers in accessing university-generated research and expertise, resulting in fewer collaborative patents. Therefore, geographic proximity to universities partially boosts enterprise innovation by promoting increased collaborative patenting.

Table 8
Mechanism Test 1: University-Enterprise Collaboration Patents

	(1) Co_Patent	(2) Co_Patent
Distance	-0.007***	-0.009***
	(-3.099)	(-3.548)
Growth		-0.003**
		(-2.141)
LEV		-0.066**
		(-2.102)
PPE		0.051*
		(1.743)
CapEx		0.117*
		(1.786)
Size		0.040***
		(3.650)
Indep		-0.002
		(-0.056)
GDP		-0.025*
		(-1.762)
Population		0.030**
		(2.094)
Edu_ratio		-0.008
		(-0.091)
City FE	Y	Y
Year FE	Y	Y
_cons	0.082***	-0.773**
	(13.219)	(-2.399)
N	31097	31097
R2	0.021	0.054

Note: This table presents regression results analyzing the effect of geographic distance on university-enterprise collaboration patent counts for listed companies over the period 2010–2022. All regressions are adjusted for clustering at the city level. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Table 9 demonstrates that the coefficient for Distance regarding the proportion of innovation-related keywords in annual reports is significantly negative at the 1% level. This result suggests that enterprises located farther from universities are less likely to emphasize innovation-related disclosures in their annual reports. Economically, this outcome could reflect two potential explanations: enterprises genuinely prioritizing technological innovation, or enterprises aiming to signal such prioritization to external investors. Genuine prioritization directly enhances innovation outputs. Conversely, if enterprises utilize innovation disclosures primarily for signaling without correspondingly increasing actual innovation investments, they risk negative market reactions due to unmet investor expectations, potentially harming firm value. Consequently, even when signaling motivations dominate, firms retain incentives to proactively increase actual innovation outputs.

Table 9
Mechanism Test 2: Proportion of Innovation-related Keywords in Annual Reports

	(1)	(2)
	Percentage_Report	Percentage_Report
Distance	-0.001***	-0.001***
	(-2.718)	(-2.629)
Growth		0.000
		(0.516)
LEV		-0.004*
		(-1.732)
PPE		-0.002
		(-0.524)
CapEx		0.012*
		(1.664)
Size		-0.000
		(-0.689)
Indep		-0.000
		(-0.065)
GDP		0.006
		(1.306)
Population		-0.010**
		(-2.024)
Edu_ratio		0.013
		(0.681)
City FE	Y	Y
Year FE	Y	Y
_cons	0.030***	0.043
	(17.101)	(0.840)
N	30794	30794
R2	0.009	0.009

Note: This table presents regression results assessing the impact of geographic distance on the proportion of innovation-related keywords in annual reports for listed companies from 2010 to 2022. All regressions are adjusted for clustering at the city level, with significance at the 1%, 5%, and 10% levels denoted by ***, **, and *, respectively.

The mechanism analysis discussed above reveals that enterprises located closer to universities are more inclined to collaborate on patents, generating greater patent outputs. Additionally, these firms tend to emphasize innovation more explicitly in their annual disclosures. Conversely, enterprises situated farther from universities incur higher costs to access collaborative opportunities, resulting in lower emphasis on innovation disclosures and reduced innovation outputs. These findings support Hypotheses 2 and 3, elucidating the mechanisms through which geographic distance influences corporate innovation.

5.5 Heterogeneity Analysis

This section investigates heterogeneity in the relationship between enterprise-university geographic distance and innovation outputs based on city characteristics.

Initially, the sample is segmented by city size: enterprises in first-tier or new first-tier cities comprise the “large city” group, while those in smaller cities constitute the “small city” group, and the results are shown in Table 10. The classification of new first-tier cities follows the definition proposed by CBN Weekly, a Chinese business media outlet, which includes Chengdu, Hangzhou, Chongqing, Suzhou, Wuhan, Xi'an, Nanjing, Changsha, Tianjin, Zhengzhou, Dongguan, Wuxi, Ningbo, Qingdao, and Hefei. Results indicate a significantly negative coefficient on Distance within the small city group, whereas the coefficient in the large city group is not statistically significant. This difference may reflect the limited innovation resources and weaker infrastructure in smaller cities, making enterprises in these regions more sensitive to university-generated knowledge spillovers and geographic proximity. Thus, geographic proximity to universities has a more pronounced impact on innovation outputs in smaller cities. The significance of the difference between large and small city groups is confirmed through bootstrap-derived P-values based on 1,000 iterations.

Table 10
Heterogeneity Test 1: Large or small cities

	(1) Large city	(2) Small city
Distance	-0.035	-0.075***
	(-0.906)	(-3.637)
P-Value	0.000***	
Growth	-0.002	-0.006
	(-0.239)	(-0.966)
LEV	-0.837***	-0.672***
	(-5.447)	(-5.097)
PPE	-0.188	-0.353**
	(-0.861)	(-2.192)
CapEx	3.456***	1.964***
	(4.964)	(5.256)
Size	0.180***	0.236***
	(6.839)	(6.461)
Indep	0.207	0.403
	(0.467)	(1.065)
GDP	-0.012	-0.038
	(-0.080)	(-0.368)
Population	0.045	0.501***
	(0.342)	(2.875)
Edu_ratio	-0.086	-0.707
	(-0.130)	(-1.099)
City FE	Y	Y
Year FE	Y	Y
_cons	-3.099*	-7.051***
	(-1.852)	(-5.083)
N	17729	13368
R2	0.108	0.232

Note: This table presents regression results examining the impact of geographic distance on invention patent counts for listed companies from 2010 to 2022. All regression analyses are adjusted for clustering at the city level, with significance at the 1%, 5%, and 10% levels denoted by ***, **, and *, respectively. The P-values testing differences between group coefficients are calculated using 1,000 bootstrap iterations.

Second, the samples are segmented based on whether cities host a “985” university, which refers to high-level institutions prioritized and extensively supported by the Chinese government to foster the development of world-class universities. These universities represent the pinnacle of higher education in China. The results are shown in Table 11. In cities without “985” universities, geographic distance has a significantly negative impact on enterprise innovation outputs, whereas this effect is not statistically significant in cities with “985” universities. Given that “985” universities are predominantly located in major cities, this result is consistent with the findings reported in Table 10. Enterprises in regions lacking robust research infrastructure exhibit heightened sensitivity to proximity to universities, underscoring the importance for local governments and enterprises in these areas to leverage university knowledge spillovers effectively. The statistical significance of differences between cities with and without “985” universities is confirmed through bootstrap-derived P-values based on 1,000 iterations.

Table 11

Heterogeneity Test 2: Presence of “985” Universities

	(1) 985 cities	(2) Non-985 cities
Distance	-0.027	-0.090***
	(-0.828)	(-3.979)
P-Value	0.000***	
Growth	-0.001	-0.007
	(-0.155)	(-1.076)
LEV	-0.909***	-0.532***
	(-6.646)	(-3.953)
PPE	-0.251	-0.287
	(-1.279)	(-1.426)
CapEx	3.397***	2.057***
	(4.849)	(5.494)
Size	0.181***	0.241***
	(7.349)	(5.830)
Indep	0.253	0.336
	(0.621)	(0.760)
GDP	0.086	-0.058
	(0.630)	(-0.479)
Population	0.130	0.309
	(1.021)	(1.648)
Edu_ratio	-0.265	-1.076
	(-0.412)	(-1.608)
City FE	Y	Y
Year FE	Y	Y
_cons	-4.619**	-5.637***
	(-2.784)	(-3.464)
N	18527	12570
R2	0.114	0.236

Note: This table reports regression results examining the effect of geographic distance on invention patent counts for listed companies from 2010 to 2022. All regressions are clustered at the city level, with significance levels at 1%, 5%, and 10% denoted by ***, **, and *, respectively. P-values testing the differences between group coefficients are calculated using 1,000 bootstrap samples.

Third, the sample is categorized based on administrative levels—municipalities (Beijing, Shanghai, Tianjin, and Chongqing), sub-provincial cities (Guangzhou, Shenzhen, Chengdu, Hangzhou, Ningbo, Wuhan, Xi'an, Nanjing, Jinan, Xiamen, Qingdao, Dalian, Shenyang, Changchun, and Harbin), and prefecture-level cities. In China, administrative hierarchy significantly impacts resource allocation, policy support, and development opportunities. Cities at higher administrative levels generally receive more substantial financial resources, favorable policies, and infrastructure investments, potentially influencing interactions between universities and enterprises. Results presented in Table 12 indicate statistically significant effects only within prefecture-level cities, aligning with findings from the initial heterogeneity analysis. This suggests that geographic distance from universities does not significantly impact innovation outputs in larger cities. However, given the prevalence of enterprises in prefecture-level cities, these findings continue to offer meaningful economic implications.

Table 12
Heterogeneity Test 3: City Administrative Hierarchy

	(1) Municipality	(2) Sub-provincial	(3) Prefecture-level
Distance	0.028	-0.033	-0.112***
	(0.335)	(-0.668)	(-4.364)
Growth	-0.016	0.019*	-0.006
	(-1.302)	(2.114)	(-0.723)
LEV	-1.039**	-1.098***	-0.646***
	(-4.481)	(-7.287)	(-3.537)
PPE	0.503	-0.645***	-0.335
	(1.138)	(-3.279)	(-1.440)
CapEx	4.816**	3.738***	1.862***
	(5.356)	(3.350)	(4.888)
Size	0.184**	0.114***	0.276***
	(4.120)	(3.485)	(6.747)
Indep	0.787	0.534	0.240
	(0.766)	(0.934)	(0.510)
GDP	0.150**	0.166	-0.134
	(3.248)	(0.879)	(-0.845)
Population	1.942**	0.031	0.325
	(3.516)	(0.260)	(1.530)
Edu_ratio	-3.887	-0.334	-1.407*
	(-1.883)	(-0.490)	(-1.788)
City FE	Y	Y	Y
Year FE	Y	Y	Y
_cons	-17.767**	-2.639	-5.226**
	(-4.243)	(-1.347)	(-2.576)
N	7242	10347	13508
R2	0.111	0.121	0.257

Note: This table reports regression results examining the impact of geographic distance on invention patent counts for listed companies from 2010 to 2022. All regressions are adjusted for clustering at the city level. Significance levels at 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

The heterogeneity analysis reveals significant variations in the influence of enterprise-university geographic distance on innovation outputs across different city categories. In larger cities characterized by substantial economic resources, extensive populations, or superior university infrastructure, enterprises distant from universities may partially mitigate reduced knowledge spillovers through alternative channels, thus diminishing the negative effects associated with geographic distance. In contrast, enterprises located in smaller cities or regions lacking robust economic resources and high-quality universities exhibit greater reliance on nearby academic institutions for accessing knowledge and talent. Consequently, the benefits derived from geographic proximity are more pronounced in these areas, significantly boosting innovation outputs.

6. Conclusion

This paper investigates the relationship between geographic distance from universities and corporate innovation outputs using panel data from Chinese A-share listed companies spanning 2010 to 2022. A multivariate regression model, incorporating multiple control variables as well as enterprise and year fixed effects, is employed to mitigate potential omitted variable bias. To explore the internal mechanisms underlying the impact of geographic distance on innovation outputs, analyses are conducted focusing on “university-enterprise collaboration” and “innovation information disclosure.” Additionally, heterogeneity analyses are performed by categorizing cities to investigate variations in these effects. Robustness checks using alternative data sources further reinforces the reliability of the empirical findings.

Key findings of this study are as follows: First, baseline regression results demonstrate a significant negative relationship between geographic distance to universities and enterprise innovation outputs, suggesting that closer proximity enhances innovation performance. Second, mechanism analyses reveal that geographic proximity increases the volume of collaborative patents between universities and enterprises and encourages greater emphasis on innovation disclosures, thereby effectively boosting innovation outcomes. Third, heterogeneity analyses indicate that the positive impact of geographic proximity is especially pronounced in cities with smaller economic scales, populations, or limited university resources. Hence, local governments and enterprises in these regions should proactively utilize university knowledge spillovers to stimulate innovation.

This research contributes to the empirical literature on spatial knowledge spillovers and addresses existing gaps concerning the effects of geographic distance on corporate innovation outcomes. Furthermore, the study provides valuable empirical insights to inform policymaking aimed at enhancing enterprise innovation and guiding enterprises in strategic location decisions.

Author Contributions

The author independently performed the conceptualization, methodology, data curation, formal analysis, investigation, writing—original draft preparation, writing—review and editing, visualization, supervision and project administration. The author has read and agreed to the published version of the manuscript.

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Data Availability Statement

The data used in this study were obtained from multiple publicly accessible databases and official sources, with details as follows: Firm-level data: Financial, governance, and other corporate characteristics data were primarily sourced from the CSMAR (China Stock Market & Accounting Research) Database (https://www.gtarsc.com/) and the CNRDS (Chinese Research Data Services) Database (https://www.cnrds.com/). Innovation data: Patent records were obtained from the China National Intellectual Property Administration (CNIPA) official website (https://pss-system.cnipa.gov.cn/). University-related data: Higher education institution information was collected from China Education Online (https://www.gaokao.cn/school/search?fromcoop=pddh). City level data: Macroeconomic indicators and other urban characteristics were sourced from the National Bureau of Statistics of China (https://data.stats.gov.cn/) and the CSMAR Database (https://www.gtarsc.com/). The analytical datasets (including the final sample, key variables, etc.), processed using Stata statistical software (Stata) for cleaning, merging, and computation, have been publicly archived on Zenodo with a permanent Digital Object Identifier (DOI): 10.5281/zenodo.16753853.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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