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Innovation Element Agglomeration and Enterprise Green Innovation: Mechanism Analysis Based on Cost Effect and Factor Matching Effect

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Abstract

Innovation elements are underexplored in terms of their role and mechanisms in driving corporate innovation. Using panel data for Chinese A-share listed firms from 2011 to 2023, this study examines how city-level innovation element agglomeration affects firm-level green innovation. The results show that agglomeration significantly promotes firms' green innovation, a finding that remains robust across multiple robustness checks. Mechanism analysis reveals two channels: the cost effect, which lowers debt financing costs and institutional transaction costs; and the factor-matching effect, which alleviates factor market distortions and credit misallocation. Heterogeneity analysis further indicates that the effect is stronger for labor-intensive firms, firms with high financing constraints, and firms located in key environmental protection cities and innovative cities. This study extends the literature on the spatial allocation of innovation elements and offers practical implications for optimizing regional policies to foster green innovation and sustainable development.

Keywords: agglomeration of innovative elements; green innovation; cost effect; element matching effect

1. Introduction

As green development strategies continue to advance, green innovation by enterprise firms has become a major pathway to high-quality development and sustainability. Unlike conventional technological upgrading, green innovation requires substantial R&D investment, costly equipment replacement, and long adjustment periods. It also involves considerable uncertainty. As a result, many firms face serious obstacles, including limited innovation resources, heavy financing pressure, high transformation costs, and weak internal motivation [1–3]. In this context, the advancement of green innovation in enterprises depends not only on firms' own resource endowments and capabilities but also on support from the external innovation environment and the factor supply system.

Compared with traditional production factors, the agglomeration of innovation elements is more closely associated with the construction of innovation capacity, the diffusion of technology, and the formation of collaborative networks, all of which are vital for sustainable development and the low-carbon transition. By improving resource allocation, strengthening regional innovation systems, and fostering collaborative innovation, the spatial concentration of innovation elements may create favorable conditions for firms' green



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innovation. It may thus serve as a crucial external force driving the green transformation of the manufacturing sector [4,5]. Against this background, this study investigates the relationship between innovation element agglomeration and corporate green innovation. In particular, it seeks to answer three key questions: Does innovation element agglomeration significantly promote firms' green innovation? Through what mechanisms does this effect operate? And does the effect vary across different firm types and institutional contexts?

The existing literature has extensively explored the determinants of green innovation. A large body of research builds on the Porter hypothesis, which posits that well-designed environmental regulations can stimulate both economic growth and environmental improvement through an innovation compensation effect [6,7]. Building on this perspective, scholars have further examined how different types and intensities of environmental regulation affect green innovation, exploring issues such as regulatory stringency, regulatory design, and non-linear effects. For instance, Li and Tao (2012) [8] identified a U-shaped relationship between environmental regulation and industrial green total factor productivity. Lei et al. (2020) [9] found that command-and-control and voluntary regulations can significantly promote green innovation once they exceed certain thresholds. In addition, gradual technological upgrading, digital transformation, and artificial intelligence have been shown to exert significant effects on the green innovation of manufacturing firms [10–12]. Overall, however, the existing studies have concentrated on discrete external shocks such as institutional constraints or technological change, paying insufficient attention to broader and more systematic external conditions, particularly the spatial agglomeration of innovation elements. This study addresses that gap by examining how innovation element agglomeration promotes green innovation, with a specific focus on the cost-reduction and factor-allocation mechanisms.

Meanwhile, research on the agglomeration of innovation elements has also made substantial progress. Since geographic factors were incorporated into economic analysis, the spatial agglomeration of innovation elements and its economic consequences have attracted growing scholarly attention. Existing studies generally suggest that innovation element agglomeration involves not only the static distribution of innovation resources and innovation actors, but also a dynamic process of factor flows, reorganization, and spatial reallocation [13]. The related literature has mainly developed along two lines: measurement and evaluation, and economic consequences. In terms of measurement, some studies focus on the overall agglomeration of multiple innovation elements, whereas others examine the localized concentration of individual elements. Common methods include the entropy method, factor analysis, and improved location quotient measures [14–16]. With respect to economic consequences, existing research shows that the agglomeration of innovation elements can improve regional innovation performance, promote industrial upgrading, and stimulate regional economic growth [4,17,18]. However, whether innovation element agglomeration generates a green innovation effect has not yet been systematically examined. In particular, little is known about its impact on the green innovation of firms at the micro level or the mechanisms through which this effect operates.

To fill the gap, this study examines whether and how innovation element agglomeration facilitates firms' green innovation. Using panel data on Chinese A-share listed firms from 2011 to 2023, it analyzes the effect of city-level innovation element agglomeration on firm-level green innovation and investigates the underlying transmission channels. It further explores the heterogeneous effects across different types of firms and institutional environments.

This study makes three primary contributions to the literature. First, it extends research on innovation element agglomeration from the regional macro-level to the firm micro-level, revealing the transmission pathways through which spatial factor concen-

tration drives corporate green innovation. Second, it identifies and empirically tests two distinct mechanisms—the cost effect and the factor-matching effect—thereby enriching the analytical framework of green innovation drivers. Third, through heterogeneity analysis, it reveals the boundary conditions of this effect, providing empirical evidence for differentiated policy design. More broadly, the findings of this study not only expand the research frontier on the economic consequences of innovation element agglomeration but also offer valuable insights into how to leverage spatial factor allocation to advance corporate sustainability.

The remainder of this study is organized as follows. Section 2 presents the theoretical analysis and research hypotheses. Section 3 describes the empirical model, variable definitions, and data sources. Section 4 reports the benchmark regression results and a series of robustness tests. Section 5 conducts mechanism analysis and heterogeneity discussion. Section 6 concludes the study and proposes corresponding policy implications.

2. Theoretical Analysis and Research Hypothesis

This study integrates three theories to explain how innovation element agglomeration drives enterprise green innovation through two channels: cost reduction and factor matching optimization. First, agglomeration economics [19] posits that spatial concentration yields externalities through sharing, matching, and learning, creating the essential infrastructure for co-location of innovation factors. Second, knowledge spillover theory [20] emphasizes that non-rival knowledge diffuses through informal contacts and labor mobility, accelerating firms' learning, recombination, and adoption of green technologies. Third, transaction cost economics [21] highlights that dense networks mitigate information asymmetries and contracting frictions, thereby reducing both explicit and implicit costs of green innovation. Together, they form the theoretical scaffolding for the hypotheses.

2.1. The Agglomeration of Innovative Elements and Green Innovation of Enterprises

Green innovation is characterized by high investment, long cycles, and significant uncertainty. Its successful realization therefore depends not only on firms' internal resource endowments and capabilities [22] but also on external factors, such as environmental regulations and the broader factor supply system [23–25]. This study argues that the efficient spatial and industrial agglomeration of innovation elements bridges these internal capabilities with the external environment, thus serving as a core engine for the green innovation of the manufacturing sector.

Specifically, the agglomeration of innovation elements affects corporate green innovation through several key pathways. First, spatial concentration fosters shared infrastructure, specialized division of labor, and economies of scale, which lower R&D, production, and coordination costs, and improve resource allocation. Second, clustering enhances the flow and diffusion of knowledge, technology, and information both among firms and between firms and research institutions; this reduces the cost of acquiring external green knowledge, accelerates learning, absorption, and re-innovation. Third, agglomeration gives firms easier access to and integration of critical resources—such as high-skilled talent, advanced technologies, R&D funding, and data—thereby strengthening their green innovation capabilities and production capacity. Fourth, the dense networks formed by agglomeration reinforce collaborative links among firms, financial institutions, and intermediaries, improving the effectiveness of joint R&D, technology transfer, and financial support.

In conclusion, innovation element agglomeration facilitates the continuous accumulation, flow, integration, and optimal allocation of capital, talent, technology, and data within a region. This, in turn, enhances firms' green innovation capabilities, improves resource

utilization efficiency, and elevates environmental governance standards. Based on this, this study proposes Research Hypothesis 1.

Hypothesis 1. *The agglomeration of innovation elements can significantly promote the green innovation of enterprises.*

2.2. The Agglomeration of Innovative Elements, Cost Effect and the Green Innovation of Enterprises

Firms face dual constraints during their green innovation: explicit and implicit costs. On one hand, explicit costs involve substantial capital investments in green production processes, low-carbon R&D, and equipment upgrades [26]. On the other hand, implicit costs arise from information searching, technology learning, organizational coordination, and financing [27,28]. When these costs become prohibitive, firms' incentives for green investment and innovation are significantly dampened, weakening the internal drive for innovation. Therefore, examining whether innovation element agglomeration can exert a cost effect by mitigating these burdens is essential to understanding its role in promoting the green innovation of enterprises.

On the one hand, the agglomeration of innovation elements reduces the explicit costs of green innovation. Agglomeration economies lower per-unit input costs for green production upgrades, environmental remediation, and technological retrofitting. Moreover, by strengthening firms' innovation capabilities, growth prospects, and market transparency, agglomeration mitigates information asymmetries and thereby reduces the risk premiums demanded by financial institutions. This eases the financing constraints that typically impede green innovation, given its large scale, long payback periods, and high risk [29,30].

On the other hand, innovation agglomeration lowers the implicit costs of green innovation through three interrelated mechanisms. First, knowledge spillover accelerates the diffusion of technical know-how and best practices, reducing search, learning, and trial-and-error costs. Second, network ties with universities, research institutes, financial institutions, and supply-chain partners enhance collaborative efficiency in R&D, commercialization, and production transformation, cutting communication, negotiation, monitoring, and coordination costs [31]. Third, agglomeration improves bank-firm information flows and financial resource allocation, alleviating hidden constraints such as slow credit approval, financing delays, and mismatched loan terms caused by credit misallocation.

Furthermore, it can be seen that the agglomeration of innovation elements can not only reduce the explicit costs in firms' green innovation, but also lower their implicit costs, thereby enhancing firms' capacity and motivation to implement green innovation and generating a significant cost effect. Accordingly, this study proposes Research Hypothesis 2.

Hypothesis 2. *The agglomeration of innovation elements promotes the green innovation of enterprises through the cost effect channel, i.e., by reducing both explicit costs and implicit costs.*

2.3. The Agglomeration of Innovative Elements, Factor Allocation Effect and the Green Innovation of Enterprises

The green innovation of firms is shaped not only by cost changes, but also by the extent to which key production factors—such as capital, labor, technology, and data—can flow efficiently and be properly matched. If these factors cannot be directed to firms with higher green production efficiency and stronger green innovation capabilities, green innovation may be hindered by resource misallocation. Therefore, whether innovation element agglomeration can generate a factor-matching effect by improving the allocation and matching

efficiency of production factors represents another important pathway through which it promotes the green innovation of enterprises.

Specifically, the agglomeration of innovation elements enhances factor allocation efficiency within firms through three channels.

First, agglomeration facilitates capital deepening by optimizing the capital–labor input structure. Green innovation requires a shift from pollution-intensive, low-efficiency production to clean, automated processes. By concentrating advanced equipment, digital technologies, and skilled labor, agglomeration encourages the rational substitution of capital for inefficient labor, raising the capital–labor ratio and strengthening firms’ green production capacity. This process not only upgrades technological sophistication but also enables the adoption of cleaner, more energy-efficient techniques essential for transformation.

Second, agglomeration alleviates factor distortions by improving firms’ access to and integration of critical resources—capital, technology, talent, and data. The presence of specialized financial intermediaries and innovation-oriented policies reduces search and transaction costs, making R&D funding and industrial support more readily available. Concurrently, knowledge spillovers and labor mobility raise workforce skill levels and better align them with the evolving demands of green manufacturing, further easing resource mismatches.

Third, agglomeration strengthens regional innovation networks, improving the matching efficiency of technology, talent, capital, and data. By channeling factors toward firms with higher green productivity, these networks foster multi-factor synergistic allocation. The co-location of complementary resources and frequent inter-organizational interactions reduce coordination frictions, accelerate the reallocation of inputs to their most productive uses, and create virtuous cycles.

From a practical perspective, China’s manufacturing industry has long relied on a development model based on low-cost labor and high resource consumption, leading to low resource allocation efficiency and significant environmental governance pressure [32,33]. As the demographic dividend diminishes, factor costs rise, and green development constraints intensify, the traditional extensive growth model has become increasingly unsustainable. The agglomeration of innovation elements helps enhance total elements productivity and green development capacity by promoting capital deepening, facilitating the upgrading of human capital, and alleviating capital–labor mismatches, thereby providing sustained momentum for the green innovation of enterprises.

In summary, the agglomeration of innovation elements can significantly improve the resource allocation of enterprises by optimizing the structure of capital–labor input and alleviating distortions in capital and labor factors, thereby promoting the green innovation of enterprises. Accordingly, this study proposes Research Hypothesis 3.

Hypothesis 3. *The agglomeration of innovation elements promotes the green innovation of enterprises through the factor-matching effect channel, i.e., by improving capital–labor input structures, alleviating factor market distortions, and facilitating multi-factor synergistic allocation.*

3. Research Design

To provide a clear overview of the overall research logic, Figure A1 (see Appendix A) systematically illustrates the complete pathway from data and measurement, empirical tests to mechanism analysis and heterogeneity analysis. Based on this framework, the following subsections elaborate on the model specification and variable definitions.

3.1. Empirical Model

This study adopts the two-way fixed effects model to investigate the promoting effect of the agglomeration of innovation elements on the green innovation of enterprises, and constructs the following benchmark model:

$$green_innov_{jit} = \alpha_0 + \alpha_1 Agglomit_{jt} + \sum_j \alpha_j Control_{jit} + \eta_t + \lambda_i + \varepsilon_{it} \quad (1)$$

In Equation (1), i , j , and t denote enterprises, cities, and years, respectively; $green_innov_{jit}$ represents firms' green innovation; $Agglomit_{jt}$ is the core explanatory variable, denoting the agglomeration of innovation elements; $Control_{jit}$ represents the set of control variables; α_0 , α_1 , α_j denote the coefficients to be estimated; η_t represents year fixed effects; λ_i represents enterprise fixed effects; and ε_{it} denotes the random disturbance term.

3.2. Variable Descriptions

3.2.1. The Dependent Variable

The study measures the green innovation of enterprises by adding one to the total number of green patent applications and taking the natural logarithm. The larger this indicator is, the more green innovation output formed by the enterprise's unit R&D investment, and the higher the level of green innovation.

3.2.2. The Independent Variable

According to the "Opinions on Establishing a More Perfect Mechanism for Market-based Allocation of Factors" issued by the Central Committee of the Communist Party of China and the State Council in 2020, land, labor, capital, technology, and data are all important elements in modern economic operation. Among them, the resource collection that can directly contribute to technological progress, knowledge creation, and industrial upgrading can be regarded as innovation elements. This study defines the agglomeration of innovation elements as the process under the joint influence of policy guidance, market allocation, and institutional guarantee, in which innovative talents, research and development capital, technological achievements, and data resources continuously gather in a specific region and achieve coordinated allocation. Its core feature lies in the spatial agglomeration of innovation resources and the resulting knowledge spillover, resource integration, and system optimization effects [34].

Drawing on Xiang's (2025) [35] research, this study synthesizes innovation factor agglomeration indicators using the entropy method across four dimensions: innovation talent, capital, technology, and data. The specific indicator construction is shown in Table 1. Specifically, innovation talent serves as the intellectual source of innovation activities; R&D capital provides the material foundation for innovation investment; technological outputs represent the direct manifestation of innovation outcomes; and data elements connect the other three dimensions and enhance innovation efficiency.

3.2.3. The Control Variables

The set of control variables in this study (*Control*) comprises two categories of indicators: regional characteristics and firm-level characteristics. First, regional-level control variables. It selected industrial structure (*indus*), economic development level (*pgdp*), and environmental regulations (*envir_protect*) for 261 prefecture-level cities from 2011 to 2023. Second, firm-level control variables. It selected firm characteristics of listed manufacturing companies from 2011 to 2023, including enterprise size (*size*), enterprise age (*lnage*), asset-liability ratio (*leverage*), and return on assets (*ROA*). The definitions of the main variables in this study are shown in Table 2.

Table 1. Aggregation index construction of innovation factor agglomeration.

Level 1 Indicators	Level 2 Indicators	Level 3 Indicators
The agglomeration of innovation factors	talent element	Percentage of R&D Personnel in the Workforce
		Number of College Students per 10,000 People
		Share of Science and Technology Expenditures in Public Fiscal Expenditures
	capital element	Ratio of Financial Institutions' Outstanding Deposits and Loans to GDP
	technological element	Number of Granted Invention Patents per 10,000 People
		Number of Granted Design Patents per 10,000 People
		Number of Granted Utility Model Patents per 10,000 People
	data element	Number of Mobile Phones per 10,000 People
		Number of Broadband Internet Subscribers per 10,000 People
		Volume of Telecommunications Services per 10,000 People

Table 2. Definitions of variables.

Variable Type	Variable	Variable Symbols	Definition
The dependent variable	Green innovation	<i>green_innov</i>	$\ln(\text{Number of Green Invention Patent Applications Filed by Enterprises} + 1)$
The independent variable	The agglomeration of innovation elements	<i>Agglomit</i>	Measure using the Entropy Method
The control variables	Industrial structure	<i>indus</i>	The proportion of the secondary industry in the regional GDP
	Economic development level	<i>pgdp</i>	The natural logarithm of per capita regional GDP
	Environmental regulations	<i>envir_protect</i>	Number of environmental protection terms/Total word count of the work report (Based on the government report's elaboration on environmental protection work, this article has selected 27 environmental protection terms that can comprehensively reflect the government's emphasis on environmental protection, such as environmental protection, green, clean, ecological, low-carbon, energy conservation, emission reduction, and pollutant discharge.)
	Enterprise size	<i>size</i>	The logarithm of the total assets of the enterprise
	Enterprise age	<i>lnage</i>	$\ln(\text{Current Year} - \text{Establishment Year})$
	Asset-liability ratio	<i>leverage</i>	Total liabilities of the enterprise/Total assets of the enterprise
	Return on Assets	<i>ROA</i>	Net profit of the enterprise/Total assets of the enterprise

3.3. Data Source and Explanation

This study uses Chinese A-share listed firms from 2011 to 2023 as the research sample. The sample period is chosen because China steadily promoted green development and innovation-driven development during these years, providing an appropriate institutional and practical context for this analysis.

Firm-level data were obtained from the CSMAR database, while city-level data were sourced from the China City Yearbook. To ensure the accuracy of the empirical results, the original data were processed as follows: (1) Companies with listing statuses marked as ST, *ST, PT, suspended, or delisted were excluded, retaining only those with normal

listing statuses; (2) Companies listed in the same year were excluded to avoid discrepancies in information disclosure caused by a short listing period; (3) Samples with severe data missingness were excluded, resulting in a final sample of 37,759 observations. Descriptive statistics for the main variables in this study are presented in Table 3.

Table 3. Descriptive statistics of key variables.

Variable	Mean	SD	Min	Max	N
<i>green_innov</i>	0.600	1.006	0.000	4.500	37,759
<i>Agglomit</i>	0.119	0.131	0.002	0.639	37,759
<i>lnage</i>	2.865	0.358	1.792	3.526	37,759
<i>size</i>	22.217	1.516	19.165	27.439	37,759
<i>leverage</i>	0.423	0.215	0.050	0.925	37,759
<i>ROA</i>	0.038	0.065	−0.252	0.208	37,759
<i>indus</i>	38.974	11.497	14.910	63.430	34,401
<i>pgdp</i>	11.521	0.506	10.069	12.223	34,374
<i>envir_protect</i>	0.003	0.001	0.001	0.007	32,123

4. Empirical Analysis

4.1. Analysis of the Benchmark Regression Results

Table 4 presents the benchmark regression results. The estimation result in column (1) indicates that, without including control variables, the impact coefficient of the agglomeration of innovation elements on the green innovation of enterprises is 0.186, which is significant at the 1% statistical level. The estimation results in columns (2) and (3) show that, after adding enterprise-level and city-level control variables, respectively, the impact coefficient of the agglomeration of innovation elements on the green innovation of enterprises is 0.149 and 0.143, respectively, which are both significant at the 5% statistical level. This empirical result indicates that a one-standard-deviation increase in the agglomeration index is associated with an approximately 3.1% increase in green patent applications. In practical terms, this marginal contribution translates into additional green patent filings annually, which can substantially accumulate over time, enhancing firms' green technology portfolios and regional environmental performance. This regression result verifies the research Hypothesis 1, that is, the agglomeration of innovation elements can significantly promote the green innovation of enterprises.

Table 4. Benchmark regression results.

	(1) <i>green_innov</i>	(2) <i>green_innov</i>	(3) <i>green_innov</i>
<i>Agglomit</i>	0.186 *** (2.73)	0.149 ** (2.32)	0.143 ** (1.97)
<i>lnage</i>		−0.029 (−0.26)	0.026 (0.22)
<i>size</i>		0.251 *** (13.84)	0.237 *** (12.01)
<i>leverage</i>		−0.118 ** (−2.41)	−0.119 ** (−2.20)
<i>ROA</i>		0.029 (0.37)	0.031 (0.35)
<i>indus</i>			−0.002 (−1.00)
<i>pgdp</i>			0.037 (0.77)

Table 4. Cont.

	(1) <i>green_innov</i>	(2) <i>green_innov</i>	(3) <i>green_innov</i>
<i>envir_protect</i>			−6.666 (−1.39)
cons	0.578 *** (71.24)	−4.869 *** (−10.01)	−5.067 *** (−6.34)
Fixed effect of enterprise	YES	YES	YES
Fixed effect of time	YES	YES	YES
Observations	37,458	37,458	28,366
R ²	0.725	0.734	0.733

Note: The value in parentheses represents t-statistics; *** and ** indicate significance levels of 1% and 5%, respectively.

4.2. Robustness Test

4.2.1. Endogeneity Test

To alleviate the possible reverse causal relationship between the agglomeration of innovation elements and the green innovation of enterprises, this study further uses lagging explanatory variables for identification. The regression results are shown in columns (1)–(2) of Table 5.

Table 5. Endogeneity test.

	(1) <i>green_innov</i>	(2) <i>green_innov</i>
<i>lag_Agglomit</i>	0.129 * (1.80)	
<i>lag2_Agglomit</i>		0.362 *** (3.67)
<i>lnage</i>	0.133 (1.01)	0.130 (0.81)
<i>size</i>	0.255 *** (11.20)	0.275 *** (10.87)
<i>leverage</i>	−0.186 *** (−3.16)	−0.213 *** (−3.44)
<i>ROA</i>	−0.003 (−0.09)	−0.025 (−1.02)
<i>indus</i>	0.000 (0.44)	0.000 (0.63)
<i>pgdp</i>	0.023 (0.62)	0.028 (0.71)
<i>envir_protect</i>	−3.858 (−0.77)	−1.557 (−0.29)
cons	−5.649 *** (−6.94)	−6.168 *** (−6.75)
Fixed effect of enterprise	YES	YES
Fixed effect of time	YES	YES
Observations	24,016	20,611
R ²	0.761	0.776

Note: The value in parentheses represents t-statistics; *** and * indicate significance levels of 1% and 10%, respectively.

The estimation with the one-period lag shows a coefficient of 0.129 for innovation factor agglomeration, significant at the 10% level. The two-period lag yields a coefficient of 0.362, significant at the 1% level. These findings indicate that, after controlling for temporal

ordering and alleviating reverse-causality concerns, the positive effect of innovation factor agglomeration on firms' green innovation remains robust.

4.2.2. Incorporate the City Fixed Effect

To absorb time-invariant city-level characteristics and thereby mitigate endogeneity bias arising from unobserved heterogeneity across cities, while also effectively capturing the spatial attributes inherent in the agglomeration of innovation elements, this study introduces city fixed effects. The regression results are shown in column (1) of Table 6. The coefficient of innovation element agglomeration is 0.124, which is significant at the 10% level, indicating that the agglomeration of innovation elements has a positive promoting effect on the green innovation of enterprises, which is consistent with the benchmark regression results.

Table 6. Robustness test.

	(1) Incorporate the City Fixed Effect	(2) Adjust the Sample—Exclude the Municipalities Directly Under the Central Government	(3) Adjust the Sample— Special Year	(4) The Green Finance Reform and Innovation Pilot Zones	(5) National Innovation and Entrepreneurship Demonstration Bases	(6) Environmental Protection Court City Pilot Projects
<i>Agglomit</i>	0.124 *	0.152 *	0.528 ***	0.161 **	0.144 *	0.200 ***
<i>DID</i>	(1.79)	(1.90)	(4.30)	(2.14)	(1.94)	(2.60)
<i>lnage</i>	0.117	−0.012	0.175 *	0.124	0.074 ***	0.043 **
<i>size</i>	0.235 ***	0.267 ***	0.201 ***	0.247 ***	0.124	0.132
<i>leverage</i>	−0.159 ***	−0.137 **	−0.108 *	−0.166 ***	0.124	0.132
<i>ROA</i>	−0.003	−0.012	0.126 **	0.001	0.002	0.000
<i>indus</i>	0.000	0.000	0.000	0.000	0.000	0.000
<i>pgdp</i>	−0.004	−0.034	0.030	0.017	0.018	0.015
<i>envir_protect</i>	−9.177 **	−6.477	−2.220	−6.334	−4.950	−7.515
<i>_cons</i>	−4.862 ***	−4.902 ***	−4.800 ***	−5.392 ***	−5.431 ***	−5.427 ***
	(−7.95)	(−6.41)	(−6.81)	(−7.45)	(−7.53)	(−7.51)
Fixed effect of enterprise	YES	YES	YES	YES	YES	YES
Fixed effect of time	YES	YES	YES	YES	YES	YES
Fixed Effect of city	YES					
Observations	28,366	21,990	20,571	28,303	28,366	28,249
R ²	0.746	0.718	0.747	0.740	0.741	0.741

Note: The value in parentheses represents t-statistics; ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

4.2.3. Adjusting the Sample

Considering the potential overrepresentation of firms from key regions, this study excludes observations for firms located in municipalities directly under the central government and re-estimates the model. This procedure helps alleviate possible estimation bias caused by an uneven regional distribution of the sample. The results are reported in column (2) of Table 6. After excluding these observations, the coefficient on innovation factor agglomeration remains positive and statistically significant at the 10% level, with an estimated value of 0.152. This result is consistent with the baseline findings.

To account for possible interference from major external shocks, this study excludes observations from 2020 to 2023 and conducts the regression again. This adjustment is motivated by the fact that the COVID-19 pandemic and related disruptions may have affected firms' green transformation during this period. As shown in column (3) of Table 6,

the coefficient on innovation factor agglomeration remains significantly positive, which is in line with the baseline results. This finding suggests that the main conclusion does not depend on specific years and is robust to the exclusion of the pandemic period.

4.2.4. Eliminating the Interference of Concurrent Policies

To further verify the robustness of the baseline results, this study controls for the potential influence of other contemporaneous policy initiatives that may confound the estimated effect of innovation factor agglomeration.

During the sample period, several policy programs were implemented in different cities, including the green finance reform and innovation pilot zones, national innovation and entrepreneurship demonstration bases, and environmental protection court pilot projects. These policies may overlap with the spatial distribution of innovation factors and thus affect the identification of the agglomeration effect. On the one hand, such policies may facilitate the agglomeration of innovation factors by improving the local innovation environment and optimizing resource allocation. On the other hand, they may directly promote firms' green innovation through policy incentives and institutional support. If so, the estimated effect of innovation factor agglomeration may partly capture the influence of these concurrent policies.

To address this concern, this study excludes the samples affected by each of these policies and re-estimates the model. The results are reported in columns (4)–(6) of Table 6. After excluding observations associated with the three policy programs, the coefficient on innovation factor agglomeration remains positive and statistically significant. Its magnitude also stays broadly comparable to that in the baseline regression. These findings suggest that the positive effect of innovation factor agglomeration on firms' green innovation is not driven by concurrent policy shocks and remains robust.

5. Further Analysis

5.1. Mechanism Analysis

5.1.1. The Green Innovation Driven by Cost Effect

Enterprise green innovation activities are characterized by large investment scale, long payback period, and high uncertainty. Therefore, enterprises are highly dependent on funds. The aggregation of innovation elements can, by improving the regional financial ecological environment and the quality of institutional supply, reduce the external financing costs and non-productive institutional costs faced by enterprises, thereby releasing more internal resources and external capital space for green innovation. Based on this, this study selects debt financing costs and institutional transaction costs as proxy variables for the cost effect to conduct mechanism tests.

External financing is a vital source of funds for green innovation, and the cost of debt financing directly determines the affordability and availability of external capital. Referring to [36], this study measures debt financing cost as the ratio of a firm's financial expenses in the following year to its total liabilities at the end of the current period. Column (1) of Table 7 shows that the estimated coefficient of innovation element agglomeration on debt financing cost is -0.005 , significant at the 10% level. This indicates that agglomeration significantly reduces firms' cost of debt financing.

The underlying mechanism aligns with the theoretical prediction in Hypothesis 2. The agglomeration improves regional information and reduces bank-firm asymmetry through proximity and dense inter-firm networks. This enables better credit assessment and lower risk premiums, giving firms cheaper capital for green R&D and upgrades.

Table 7. Mechanism test based on cost effect and factor matching effect.

	(1) The Cost of Debt Financing	(2) The Cost of Institutional Transaction	(3) FAC	(4) The Absolute Distortion Coefficient of Labor	(5) Credit Mismatch
<i>Agglomit</i>	−0.005 * (−1.67)	−0.006 *** (−4.32)	−8.402 *** (−13.14)	−0.869 * (−1.78)	−0.125 ** (−2.23)
<i>lnage</i>	0.051 *** (9.79)	−0.004 (−1.52)	−1.781 (−1.53)	−0.387 (−0.82)	0.004 (0.07)
<i>size</i>	−0.001 (−0.94)	−0.006 *** (−12.74)	0.076 (0.40)	0.052 (0.61)	−0.058 *** (−6.41)
<i>leverage</i>	0.085 *** (24.48)	0.020 *** (12.80)	0.921 (1.50)	0.260 (0.80)	−0.237 *** (−6.40)
<i>ROA</i>	−0.012 ** (−2.33)	0.022 *** (9.03)	−1.500 (−1.55)	0.001 (0.00)	−0.417 *** (−4.78)
<i>indus</i>	0.000 *** (3.63)	−0.000 (−0.59)	0.326 *** (8.00)	−0.144 *** (−9.59)	0.000 (0.23)
<i>pgdp</i>	−0.002 (−1.19)	0.001 (0.85)	2.725 *** (3.11)	−2.178 *** (−7.56)	−0.011 (−0.43)
<i>envir_protect</i>	0.002 (0.01)	0.293 *** (2.66)	−155.674 *** (−2.59)	−19.170 (−0.63)	1.948 (0.66)
<i>_cons</i>	−0.149 *** (−5.00)	0.149 *** (8.57)	−17.400 (−1.58)	31.949 *** (7.80)	2.180 *** (5.49)
Fixed effect of enterprise	YES	YES	YES	YES	YES
Fixed effect of time	YES	YES	YES	YES	YES
Observations	25,959	16,375	28,132	28,353	28,129
R ²	0.644	0.769	0.923	0.319	0.455

Note: The value in parentheses represents t-statistics; ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

In addition, institutional transaction costs, as non-productive expenditures that enterprises bear in administrative processes, policy compliance, and contract execution, also constitute an important cost burden for enterprises' green innovation. Referring to the research of [37], the ratio of sales expenses, administrative expenses, and financial expenses to total assets is used to measure the institutional transaction costs at the enterprise level. The results are shown in column (2) of Table 7. The regression coefficient of the agglomeration of innovation elements on institutional transaction costs is −0.006, which is significant at the 1% level.

This finding supports the implicit-cost channel of Hypothesis 2. Agglomeration fosters specialized division of labor and scale economies in producer services, lowering firms' search, negotiation, and monitoring costs when dealing with regulations and contracts. Simultaneously, knowledge spillovers flatten the learning curve for policy and technical standards. By easing these hidden frictions, agglomeration frees up managerial attention and financial resources for green innovation.

5.1.2. The Green Innovation Caused by the Factor Matching Effect

The realization of green innovation in enterprises not only relies on financial support but also depends on the rational allocation of production factors. From the perspective of factor matching effects, the aggregation of innovation factors may improve the efficiency of regional factor allocation by breaking down administrative barriers, promoting information flow, and strengthening market competition, so that green innovation activities can obtain more suitable resource support. To this end, this study further selects factor market distortion, absolute distortion coefficient of labor, and credit mismatch as proxy variables for factor allocation effects.

Firstly, factor market distortion reflects the state where the overall factor resource allocation at the regional level deviates from the optimal efficiency, and it is a comprehensive indicator for measuring the efficiency of factor allocation. This study, referring to [38], adopts the relative gap between the development degree of factor markets in each region and the highest development degree of factor markets in the sample as the proxy variable for factor market distortion. In terms of substance, the key factor market twist index constructed in this text is $FAC_{it} = [\max(factor_{it}) - factor_{it}] / \max(factor_{it}) \times 100$, and the $factor_{it}$ is the index of the development degree of the factor market. The results are shown in column (3) of Table 7. The regression coefficient of the distortion of the factor market caused by the agglomeration of innovation factors is -8.402 , which is significant at the 1% level. This indicates that the aggregation of innovation elements can significantly alleviate the degree of distortion in the overall factor market of the region.

This result supports Hypothesis 3's factor-matching effect logic: reduced overall distortion allows resources to flow more freely to firms with higher green productivity. By strengthening innovation networks and inter-organizational ties, agglomeration lowers coordination frictions, accelerating and sharpening factor reallocation. Consequently, firms gain readier access to complementary inputs for green R&D and equipment renewal.

Secondly, as one of the core input factors for an enterprise's innovation activities, the allocation efficiency of labor directly determines the human resource foundation for green technology research and development. Referring to the research of [39], the absolute distortion coefficient of labor was constructed. The results are shown in column (4) of Table 7. The regression coefficient of the absolute distortion coefficient of labor caused by the agglomeration of innovation elements is -0.869 , which is significant at the 10% level. This indicates that the aggregation of innovation elements can significantly alleviate the distortion of the allocation of labor factors.

This finding supports the factor-matching channel of Hypothesis 3. The alleviation of labor distortion works through both demand and supply forces. Demand-side: agglomeration raises skilled job opportunities and green R&D wages, drawing labor into innovative sectors. Supply-side: specialized talent markets and headhunting reduce search-matching costs and improve information flows, narrowing the labor allocation gap. By mitigating these frictions, agglomeration secures the human capital needed for green innovation, enhancing firms' capacity for cleaner production and process upgrades.

Furthermore, credit mismatch, as a concrete manifestation of distorted factor allocation in the financial sector, directly affects whether green and innovative enterprises can obtain sufficient financial support. Based on this, this study further examines the impact of the aggregation of innovation elements on the degree of credit mismatch. Referring to the research of [40], this study uses the level of financial mismatch burden, that is, the deviation degree between the cost of capital utilization of enterprises and the average cost of capital utilization of the industry they are in (the average interest rate of the industry), to measure the degree of credit mismatch. The empirical results are shown in column (5) of Table 7. The estimated coefficient of the aggregation of innovation elements on the degree of credit mismatch is -0.125 , and it is significant at the 5% level, indicating that the aggregation of innovation elements can effectively alleviate credit mismatch.

This result supports Hypothesis 3. Credit misallocation stems from bank-firm information asymmetry that hinders productivity-based pricing. Agglomeration counters this via two channels: (i) geographic and supply-chain proximity enable cross-verification of firm performance through network intelligence, expanding risk assessment beyond accounting data; and (ii) information spillovers improve disclosure quality and reduce collateral reliance, sharpening credit-risk differentiation. Consequently, credit flows from low-efficiency to green-innovative firms, providing long-term transformation capital.

5.2. Heterogeneity Analysis

5.2.1. Heterogeneity Analysis by Factor Dependence

Firms' green innovation is strongly shaped by their initial factor endowments. Firms with different factor intensities often face different resource constraints, technological paths, and innovation responses. Accordingly, this study divides the sample into capital-intensive firms and labor-intensive firms based on factor intensity and then conducts separate regressions. The results are reported in Columns (1) and (2) of Table 8.

Table 8. Heterogeneity analysis based on enterprise characteristics.

	(1) Capital-Intensive Enterprises	(2) Labor-Intensive Enterprises	(3) High Financing Constraint Group	(4) Low Financing Constraint Group
	<i>green_innov</i>	<i>green_innov</i>	<i>green_innov</i>	<i>green_innov</i>
<i>Agglomit</i>	0.029 (0.26)	0.248 ** (2.48)	0.346 ** (2.42)	0.064 (0.71)
<i>lnage</i>	0.026 (0.17)	0.311 ** (1.97)	−0.311 (−1.63)	−0.127 (−0.34)
<i>size</i>	0.273 *** (8.60)	0.246 *** (10.13)	0.255 *** (6.98)	0.259 *** (9.42)
<i>leverage</i>	−0.153 * (−1.84)	−0.197 *** (−2.76)	−0.475 *** (−4.89)	−0.019 (−0.23)
<i>ROA</i>	0.024 (0.74)	−0.052 (−0.72)	0.153 * (1.70)	−0.082 (−1.20)
<i>indus</i>	−0.003 (−0.98)	0.000 (1.00)	−0.002 (−0.48)	0.000 (0.90)
<i>pgdp</i>	0.081 (1.43)	−0.077 * (−1.86)	0.075 (1.58)	−0.034 (−0.69)
<i>envir_protect</i>	−4.234 (0.60)	−10.314 (−1.56)	−0.061 (−0.01)	−5.588 (−0.86)
<i>_cons</i>	−6.273 *** (−5.71)	−4.828 *** (−5.68)	−4.867 *** (−4.28)	−4.426 *** (−3.23)
Fixed effect of enterprise	YES	YES	YES	YES
Fixed effect of time	YES	YES	YES	YES
Observations	13,291	13,442	13,474	13,231
<i>R</i> ²	0.776	0.757	0.796	0.757

Note: The value in parentheses represents t-statistics; ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

The empirical results reveal clear heterogeneity in the effect of innovation factor agglomeration on firms' green innovation. For labor-intensive firms, the coefficient on innovation factor agglomeration is 0.248 and is significantly positive at the 5% level. This result suggests that innovation factor agglomeration significantly promotes the green innovation of labor-intensive firms. By contrast, for capital-intensive firms, the estimated coefficient is statistically insignificant, indicating that the promoting effect is not evident in this group.

A possible explanation is that the stronger response of labor-intensive firms to innovation element agglomeration is primarily because these firms traditionally rely on low-cost labor competition and face more urgent "cost squeeze" pressures. The knowledge spillovers and technology diffusion facilitated by innovation element agglomeration can more quickly compensate for the technological and human capital deficiencies of such firms, thereby unleashing greater green innovation potential. In contrast, capital-intensive firms already possess relatively high technological levels and equipment bases, leaving limited marginal room for improvement through innovation element agglomeration.

5.2.2. Heterogeneity Analysis by Financing Constraints

Firms' green innovation may also vary with the degree of financing constraints they face. Firms under different financing conditions often differ in resource availability, innovation capacity, and adjustment flexibility. Accordingly, this study divides the sample into a high-financing-constraint group and a low-financing-constraint group using the mean value of the SA index as the cutoff point, and then conducts separate regressions. The results are reported in Columns (3) and (4) of Table 8.

The empirical results reveal clear heterogeneity in the effect of innovation factor agglomeration on firms' green innovation across different levels of financing constraints. For firms with high financing constraints, the coefficient on innovation factor agglomeration is 0.346 and is significantly positive at the 5% level. This finding suggests that innovation factor agglomeration significantly promotes the green innovation of firms facing relatively severe financing constraints. By contrast, for firms with low financing constraints, the estimated coefficient is statistically insignificant, indicating that the promoting effect is not evident in this group.

A possible explanation is that firms facing high financing constraints are typically "willing but unable" to pursue green innovation due to capital scarcity. Innovation element agglomeration can more significantly alleviate the "difficult and expensive financing" problems of these firms by improving the regional financial ecosystem and reducing information asymmetry and risk premiums, thereby releasing their suppressed green innovation demand. Conversely, less constrained firms, having better external finance and resource access, gain only limited marginal contributions from such agglomeration.

5.2.3. Heterogeneity Analysis by Key Environmental Protection City Status

Given the variations in the stringency of environmental regulations and the level of policy support across different cities, the impact of the agglomeration of innovation elements on firms' green innovation may exhibit significant regional heterogeneity. Based on the list of 113 key environmental protection cities published in the "Notice of the State Council on Issuing the National Environmental Protection 11th Five-Year Plan" (State Council [2007] No. 37), this study divides the sample into two groups—key environmental protection cities and non-key environmental protection cities—for separate analysis. The results are reported in Columns (1) and (2) of Table 9.

Table 9. Heterogeneity analysis based on urban characteristics.

	(1) Key Environmental Protection Cities	(2) Non-Key Environmental Protection Cities	(3) Innovative Cities	(4) Non-Innovative Cities
	<i>green_innov</i>	<i>green_innov</i>	<i>green_innov</i>	<i>green_innov</i>
<i>Agglomit</i>	0.207 ** (2.38)	0.010 (0.06)	0.150 * (1.71)	0.146 (0.98)
<i>lnage</i>	0.202 (1.60)	−0.226 (−1.44)	0.163 (1.31)	−0.098 (−0.54)
<i>size</i>	0.228 *** (10.48)	0.294 *** (8.31)	0.228 *** (10.48)	0.278 *** (7.93)
<i>leverage</i>	−0.166 ** (−2.56)	−0.178 ** (−1.97)	−0.140 ** (−2.12)	−0.229 *** (−2.61)
<i>ROA</i>	0.010 (0.34)	−0.048 (−0.55)	0.057 (0.92)	−0.028 * (−1.74)
<i>indus</i>	−0.002 (−0.47)	0.000 (0.75)	−0.001 (−0.36)	0.000 (0.70)
<i>pgdp</i>	0.001 (0.03)	−0.023 (−0.35)	0.057 (1.27)	−0.062 (−0.98)

Table 9. Cont.

	(1) Key Environmental Protection Cities	(2) Non-Key Environmental Protection Cities	(3) Innovative Cities	(4) Non-Innovative Cities
<i>envir_protect</i>	−7.779 (−1.30)	4.610 (0.63)	−8.353 (−1.39)	5.368 (0.76)
<i>_cons</i>	−4.942 *** (−6.27)	−5.018 *** (−4.80)	−5.488 *** (−6.89)	−4.660 *** (−4.33)
Fixed effect of enterprise	YES	YES	YES	YES
Fixed effect of time	YES	YES	YES	YES
Observations	21,120	7234	21,421	6927
R ²	0.748	0.727	0.746	0.732

Note: The value in parentheses represents t-statistics; ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Empirical results indicate that the promotional effect of innovation elements agglomeration on corporate green innovation is more pronounced in key environmental protection cities. In the sample of key environmental protection cities, the regression coefficient for innovation elements agglomeration is 0.207 and is significantly positive at the 5% level; whereas in the sample of non-key environmental protection cities, the corresponding estimated coefficient is not significant, suggesting that its promotional effect is primarily manifested in key environmental protection cities.

A possible explanation is that key environmental protection cities face stronger pressure for environmental governance. Stricter regulations, stronger policy support, and greater resource allocation in key environmental protection cities create an institutional environment that facilitates the translation of innovation agglomeration into green innovation. In non-key cities, weaker policies and enforcement make this effect less pronounced.

5.2.4. Heterogeneity Analysis Based on Innovative Cities

Given the systematic differences between innovative cities and non-innovative cities in terms of institutional environment, policy support intensity, and innovation infrastructure, it may affect the effect of the aggregation of innovation elements on the green innovation of enterprises. Based on whether a city is a pilot for national innovative cities, this study divided the samples into innovative cities and non-innovative cities for group testing.

The results are shown in columns (3) and (4) of Table 9. The empirical results show that the promoting effect of the agglomeration of innovation elements on the green innovation of enterprises varies significantly among different types of cities: In the sample of innovative cities, the regression coefficient of the agglomeration of innovation elements is 0.150, and it is significantly positive at the 10% level. However, in the sample of non-innovative cities, the relevant estimation coefficient is not significant, indicating that its promoting effect is mainly reflected in innovative cities.

This is because innovative cities offer stronger IP protection and incentive policies, reducing innovation risks and raising expected returns; they also host technology platforms that create dense knowledge networks, helping firms access and convert frontier green technologies into outputs. In non-innovative cities, weaker institutions, knowledge infrastructure, and financial ecosystems hinder the translation of agglomeration benefits into tangible green innovation.

6. Conclusions and Policy Recommendations

The results of this study show that innovation factor agglomeration significantly promotes firms' green innovation, thereby contributing to sustainable development.

This finding remains robust after a series of additional tests, including instrumental variable estimation.

Mechanism analysis suggests that innovation factor agglomeration affects firms' green innovation mainly through two channels. First, it generates a cost effect by reducing the cost of debt financing and institutional transaction costs, and improving firms' financing conditions, thereby lowering the cost of green innovation. Second, it produces a factor-matching effect by optimizing factor allocation and easing factor misallocation in the green innovation process, thus providing stronger resource support for firms' green upgrading.

The heterogeneity analysis further shows that this effect is not uniform across firms and regions. At the firm level, the promoting effect is more pronounced for labor-intensive firms and firms facing stronger financing constraints. At the regional level, the effect is stronger in key environmental protection cities and innovative cities. These findings suggest that the green innovation effect of innovation factor agglomeration depends on firm-level resource constraints as well as regional institutional conditions and resource endowments.

This study has several policy implications for fostering sustainability. First, policy-makers should regard innovation factor agglomeration as an important policy lever for promoting green innovation. Efforts should be made to improve the environment for the agglomeration of capital, talent, technology, and data, and to enhance mechanisms for factor mobility, sharing, and allocation. Second, policy support should focus on reducing the cost burden of firms' green innovation. Improving firms' financing environment and reducing various cost burdens during green R&D and transformation and upgrading, thereby effectively stimulating firms' motivation for green innovation. Third, greater attention should be paid to improving the allocation efficiency of innovation factors. Reforms in the market-oriented allocation of talent, technology, and data, together with better mechanisms for technology commercialization and industry–university collaboration, can strengthen the factor-matching effect of innovation factor agglomeration. Finally, policy design should be differentiated according to firm characteristics and regional conditions, so as to improve policy precision and better release the green innovation potential of innovation factor agglomeration.

7. Limitations and Future Research Directions

This study has several main limitations. First, the mechanism analysis focuses predominantly on cost and factor-matching effects, leaving other potential channels unexplored. Second, despite employing lagged explanatory variables and other robustness checks, endogeneity concerns, particularly omitted-variable bias, cannot be entirely eliminated. To strengthen causal identification, future research could adopt instrumental variable strategies or exploit quasi-natural experiments. Additionally, the sample is confined to Chinese A-share listed firms, which tend to be larger and better governed; their green innovation behavior may not reflect that of the broader SME population. Expanding the sample to include NEEQ-listed or unlisted firms would enhance the external validity of the findings.

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Appendix A

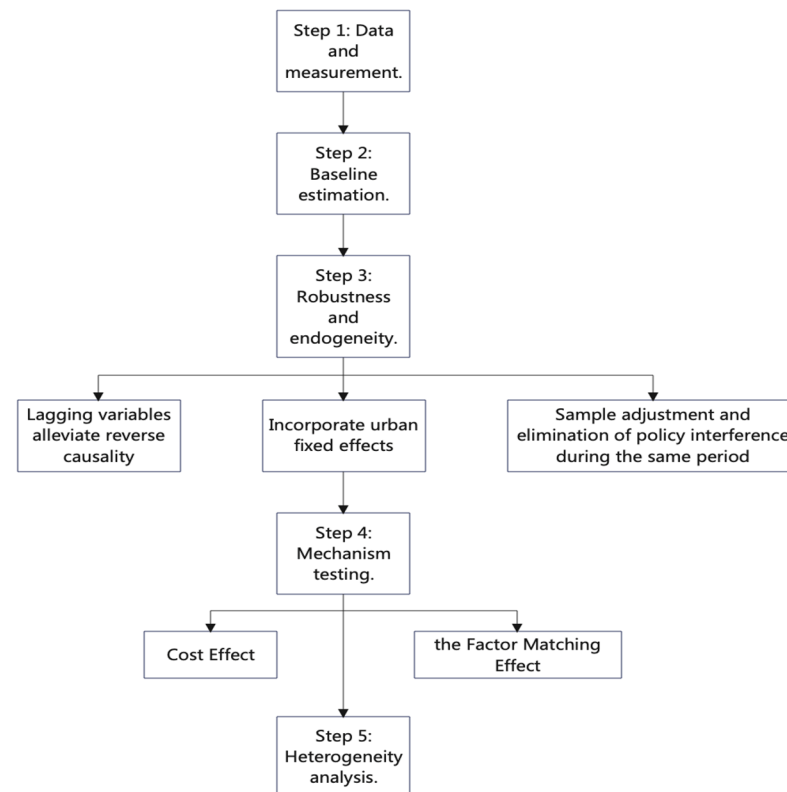


Figure A1. Overall Methodological Framework.

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