

Article

Exploring the Demand-Pull Effect on Green Innovation and Its Spatial Spillover Effects: Evidence from 261 Chinese Prefecture-Level Cities

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Abstract: In China's evolving landscape of high-quality development, characterized by a shift toward greener and lower-carbon practices, green innovation plays an essential role. Among the determinants shaping green innovation, demand factors play a pivotal role in driving its progress. Drawing on the theory of demand-induced innovation, this study utilized panel data spanning from 2008 to 2020 from 261 Chinese prefecture-level cities to investigate the effects of demand factors on green innovation. It also made use of a spatial model to investigate the regulatory function that market segmentation plays in this complex interplay, as well as any possible spatial spillover effects of these demand factors on the dynamics of green innovation. The research findings reveal that both domestic and foreign demand exert a significant fostering effect on the development of green innovation, whereas the widening income gap plays a constraining role. And the influence of demand considerations on green innovation varies depending on the region and kind of patent. Furthermore, the influence of demand factors on green innovation is accompanied by spatial spillover effects and is subject to modulation by the extent of market segmentation. The insights obtained from this research offer practical implications for advancing green innovation and provide guidance for its better promotion.

Keywords: green innovation; demand pull; spatial spillover; market segmentation



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1. Introduction

As global issues like environmental deterioration and climate change resulting from economic growth have gotten worse in recent years, nations have come to understand the significance of sustainable and green development. The United Nations incorporated sustainable development into its long-term plan through the Agenda for Sustainable Development 2030, which includes SDG 17—the Sustainable Development Goals—following the Kyoto Protocol and the Millennium Development Goals (MDGs). China, the biggest developing nation in the world, has declared its 2020 “peak carbon” and “carbon neutrality” goals. However, China is also undergoing a transition from rural to urban areas, and concerns about how to balance environmental preservation with economic growth are mounting. A key component of long-term economic growth is innovation [1,2]. Because of its qualities that safeguard the environment, green innovation, as opposed to traditional innovation, may meet the needs of green and sustainable economic development [3]. Consequently, encouraging green innovation is essential to accomplishing sustainable development goals and resolving the conflict between superior economic growth and environmental preservation [4]. The primary characteristic of green innovation is thought to be the “double externality” [2]. While the benefits of innovation can be seen in the preservation of the environment rather than in the firms themselves, the positive environmental externality allows the R&D results, in which firms have invested at a high cost, to be copied and used by others at a low cost. The incentives for businesses to invest in green innovation are impacted by both externalities [5]. It is clear that the characteristics of green innovation make it difficult for supply-side innovation subjects to fully benefit

from innovation, resulting in input potency deficiencies that, to some extent, impede the advancement and deployment of green innovation [6]. Businesses are primarily driven to innovate by their need to make money [7], and they are only motivated to introduce green ideas into the market when they see a return [8]. This is in contrast to the supply side, where demand-side needs drive expected returns. Additionally, the expansion of the market's needs, as well as the raising of standards for both demand and consumption, presents businesses with new chances to investigate creative activities and rewards, which furthers the advancement of green innovation. Therefore, in order to better support the expansion of the high-quality economy and achieve the goal of green sustainable development, it is necessary to promote green innovation at this time. This can be realized by depending on the demand for green innovation to form an effective support system. This research aims to provide a thorough analysis of the demand factors influencing green innovation, taking into account the history mentioned above.

Since the 1960s, the “demand-pull” theory has gained prominence, with Schmookler suggesting that the role of demand in innovation cannot be overlooked and presenting the viewpoint of “demand-induced innovation” [9]. In the 21st century, demand factors have increasingly attracted the attention of scholars. Numerous studies have claimed that demand factors can stimulate the development of green innovations [10–12]. However, contrasting conclusions have been drawn in some of the literature [13].

Although the academic community has developed some understanding of how demand influences green innovation, current research often overlooks income distribution due to the influence of the “consumer homogeneous preference” assumption. Foellmi and Zweimüller [14] have emphasized the central role of income distribution in shaping innovative product markets and profitability. Therefore, when discussing the impact of demand on green innovation, the influence of the demand structure is essential. In addition, existing research frequently uses survey data, often from developed countries and regions [15–17]. While survey data provide more detailed insights, using panel data for research can better capture dynamic factors and mitigate omitted-variable problems. Different countries are at different stages of economic and social development, leading to differences in the size and structure of demand between developed and developing countries. Therefore, region-specific research is essential [18]. It is worth noting that innovation activities exhibit spatial effects, with neighboring regions' green innovation activities and influencing factors affecting local green innovation [5,19]. Market segmentation exists as a means for local governments in China to pursue economic interests. However, the existing literature often neglects the adverse effects of regional market segmentation on resource allocation efficiency and enterprise innovation, which can exert a more pronounced inhibitory influence on the corporate innovation drive [20].

In summary, to address the existing research limitations, this study delved into research using data from Chinese prefecture-level cities spanning the years 2008 to 2020, which represents a finer-grained scale than previous studies, with the purpose of addressing the following research objectives: First and foremost, the aim of this research was to investigate how domestic demand structural variables, international demand, and domestic demand may affect the advancement of green innovation. Secondly, when relevant factors were found to influence the growth of green innovation in China, this study looked at whether there is variability in the region or patent type. Third, an initial examination of the implications of market segmentation was carried out, and the spatial spillover effects of demand determinants in driving green innovation were explored.

This paper makes several noteworthy innovative contributions: First and foremost, this study offers a comprehensive examination of the impact of demand on green innovation. The paper categorizes the influence of demand factors into “domestic demand” and “foreign demand”, further dissecting “domestic demand” into the “domestic demand level” and “domestic demand structure”. Secondly, this research leverages data from cities in a

developing country. Given that green innovation is intrinsically tied to the distinct economic and social contexts of different countries [21,22], the utilization of Chinese urban data in this study provides valuable insights for promoting green innovation in developing countries. Lastly, this paper delves into the impact of demand factors on green innovation from a spatial spillover perspective. Taking into consideration the backdrop of China's factor market reform and the advantages associated with using urban data, the paper aims to introduce market segmentation variables to investigate the potential moderating role of market integration when demand factors influence green innovation. This offers fresh insights into how to effectively promote green innovation, starting from the demand side.

2. Literature Review and Research Hypotheses

2.1. Literature Review

Green innovation has been receiving more and more attention since Fussler and James initially presented the idea in their groundbreaking work "Driving Eco-innovation: A Breakthrough Discipline for Innovation and Sustainability" in 1996 [23]. However, there is widespread agreement that green innovation possesses the inherent capacity to advance sustainability objectives [24]. Much of the existing research builds upon the definition put forth by Kemp, which states, "Eco-innovation is the production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organization (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives [25]".

To date, academia has extensively explored the factors influencing green innovation from various perspectives. Research from the field of technological innovation widely acknowledges the significant role of market demand in driving green innovation [16]. In the realm of management, the focus lies on corporate social responsibility, suggesting that CSR policies will encourage businesses to engage in green innovation [26,27]. Some scholars approach the topic from an institutional theory standpoint, contending that environmental regulations and the implementation of green policies impact the development of green innovation [2,28–31]. Overall, the existing literature discussing the factors influencing green innovation can be categorized into three main components: demand factors, supply factors, and environmental regulatory factors [16,32]. Demand factors primarily encompass market demand for green innovation and the environmental awareness of consumers and innovators. Supply factors pertain to the technological innovation capabilities of innovators and their ability to collaborate and access knowledge. Environmental regulations, on the other hand, refer to the policies and institutional frameworks put in place by relevant authorities to promote green innovation.

In recent years, as global environmental issues have become increasingly critical and public awareness of environmental protection has risen, demand, recognized as one of the key factors influencing green innovation activities [31], has garnered significant attention among scholars. In the following sections, this paper will review and analyze the existing literature on this subject, considering three distinct dimensions.

The initial focus of our analysis concerns studies examining the influence of levels of domestic demand on green innovation. The existing literature, including studies by Veugelers in the Flanders region of Northwestern Europe and Horbach in Germany, has consistently found that demand plays a crucial role in driving green innovation [11,12]. Veugelers, for instance, discovered that the impetus of demand is paramount in the generation of green innovation [12]. Similarly, Horbach's research, utilizing German survey data, revealed that market demand significantly propels the development of green innovation, particularly of innovative products that enhance environmental performance and production process improvements that reduce energy consumption and waste emissions [11]. Many scholars concur that consumer demand and awareness of green and environmen-

tally friendly products are central drivers of green innovation [6,33–35]. In other words, demand has a tangible impact on advancing green innovation [36,37]. However, some scholars present opposing views. Del Río, in his research on the determinants of different types of green innovation in Spain, found that neither product- nor process-based green innovations were influenced by market demand. He attributed this phenomenon to lower environmental awareness in the region and consumers' unwillingness to pay for expensive environmentally friendly goods [13]. It is evident that the research findings in this area are not entirely consistent, highlighting the need for further investigation into the impact of demand on green innovation.

Next, we explore the study of how overseas demand affects local green innovation. In the era of globalization, Stalley's research reveals that multinational corporations, leveraging their economies of scale, are better positioned to achieve local green objectives, and these multinational corporations significantly contribute to fostering local green innovation while actively pursuing these green objectives [38]. Furthermore, some scholars posit that in the current context of ongoing global market integration and the increased mobility of factors, the market itself acts as a catalyst for the development of green innovation [39,40]. As China continues its progressive development, an increasing number of Chinese brands are shifting from "trade export" to "brand export", aiming to establish an international influence. Research conducted by Q. Zhu and colleagues suggests that companies venturing into international markets, under the pressures of international environmental regulations and the demands of overseas markets, continuously enhance their competitiveness in the global market through green innovation [41]. This innovative development also aids these companies in expanding their market reach [42], thereby influencing domestic green innovation from a demand perspective. Additionally, in their study investigating the factors influencing green innovation using macroeconomic data from China, Chen and his team [10] employed total regional exports as a proxy for "foreign demand". Their research confirms that foreign market demand brings about a significantly more substantial positive stimulus to Chinese green innovation than initially anticipated. It is evident that the impact of overseas demand on the development of Chinese green innovation cannot be understated, underscoring the necessity of including foreign demand within the overall framework when researching the determinants of green innovation.

Finally, within the framework of the "demand-pull" hypothesis of innovation, not only does the level of demand influence green innovation, but the income distribution embedded within demand factors can also impact innovation. Traditional endogenous growth models tend to assume that consumers have the same income or preferences [43], and this assumption obscures the impact of income inequality as a manifestation of demand on innovation [44]. In the broader scope of innovation, Foellmi and Zweimüller argue that increasing income inequality may stimulate innovation in one aspect through the "price effect" by raising the willingness of high-income groups to pay for innovative products, but it can also inhibit innovation due to the "market size effect", which reduces the market size for innovative products [14]. The specific impact on innovation depends on the degree of the difference between these two effects. In the field of green innovation, Lorenzo Napolitano et al. suggest that income inequality and environmental issues, both global challenges, often co-occur in the same regions and are interconnected through technological innovation [45]. Income inequality is seen to have a negative impact on green innovation. Additionally, research by Zou et al. confirms the association between income inequality and green innovation [46]. The study by LI Zi-lian and Zhu Jiang-li [47] found that while the widening income gap in China initially stimulated increased innovation input to some extent, it has now crossed an "inequality threshold" and has led to a sacrifice in domestic demand, resulting in lower levels of innovation. Most of the existing literature focuses on traditional innovation in a broad sense, and the impact of income inequality on green innovation warrants further discussion.

From the analysis presented above, it is evident that previous research has examined the impact of demand factors on green innovation from various perspectives. Although these studies have provided valuable references for understanding the relationship between green innovation and its influencing factors through different theories and methods, there is still a need for more comprehensive and in-depth research that places demand factors at the core and further enriches the research sample [31]. Furthermore, given that demand is contingent on the consumer's willingness and capability to purchase, the increasing interconnectivity between regions due to the development of the transportation industry implies that demand's impact on green innovation will generate significant spatial spillover effects that cannot be ignored [48]. Thus, this study seeks to uncover the effect of demand factors on green innovation using more extensive data than prior research.

2.2. Research Hypotheses

As global environmental challenges continue to intensify, public awareness of environmental conservation is steadily increasing. Green innovation, driven by its capacity to meet ecological demands and bring about tangible benefits such as energy savings and reduced living costs, is leading to a sustained and growing consumer demand for these innovations. This evolving demand, in turn, significantly impacts the development and evolution of green innovation [49]. As long as green innovative products offer consumers cost-saving advantages and other practical benefits, demand factors will positively influence the progression of green innovation [16,50,51]. For instance, the use of green energy-efficient technologies in automobiles prompts consumers to choose such vehicles for future cost savings, thereby driving the development of related green technologies in the automotive industry. Furthermore, within the context of economic globalization, as China's economic and social development levels continue to rise and new product export trade steadily increases, environmental sustainability requirements worldwide will stimulate businesses to continuously develop green technologies with the aim of expanding overseas markets. Notably, in addition to demand levels, the demand structure also influences the development of green innovation. Low-income groups often struggle to afford innovative goods, while affluent segments tend to favor personalized and custom-made products. The widening income gap can undermine the middle-income bracket's role as the primary consumer base for green innovative products, thus hindering the progress of green innovation [52]. In summary, this paper posits the following research hypotheses:

H1a: *An increase in domestic demand will promote the growth of green innovation.*

H1b: *An increase in foreign demand will stimulate the growth of green innovation.*

H1c: *Green innovation may be impeded by the irrationality of the domestic demand structure.*

Horbach et al. (2012) identified and categorized 12 distinct types of green innovation, such as those in the materials sector, energy domain, and air pollution field, among others, and argued that various types of green innovation are influenced differently by demand factors [11]. Similarly, Demirel and Kesidou [17] conducted research following a similar approach and found that different types of green innovation are affected by different determining factors. In the realm of innovation patents in China, the application process for invention patents is lengthy and involves significant research and development challenges. Conversely, utility-model patents entail relatively few research and development difficulties and require less investment. This objective circumstance may lead to distinct responses by these two patent types when confronted with changes in demand factors. In addition to patent types, the vast geographical diversity in China, along with significant disparities in economic development levels and residents' income, plays a crucial role. These differences in economic and social development levels, along with income levels, manifest in the degree

of acceptance of green innovation by residents. In regions with higher economic and social development, residents tend to have a more detailed awareness of green environmental concerns, which is crucial in shaping the effective demand for green innovation. Given this social reality, the impact of demand factors on green innovation in China may exhibit regional variations. In summary, this paper posits the following research hypotheses:

H2a: *There is heterogeneity in the way that demand factors affect various types of green innovation.*

H2b: *Demand considerations have varying effects on green innovation in different regions.*

Consumer spending is a core factor in market demand fluctuations. Interregional population mobility and communication have enhanced due to the continuous advancement of transportation and communication technologies [53]. Regions with high demand for green products can subtly influence the green consumption levels and awareness of adjacent regions, thus elevating their green innovation levels through a “ripple effect” [19,54]. Furthermore, as the cross-regional flow of labor, capital, information, and technology intensifies, industries, population elements, and neighboring regional companies have the opportunity to better engage in the competition for local green demand, thereby leading to a spatial spillover effect of demand factors on green innovation in adjacent regions. However, it is worth noting that while demand factors may exhibit spatial spillover effects in influencing green innovation, if regional governments implement protectionist policies by artificially raising market entry barriers, it may result in increased cross-regional mobility costs for various factors. This can directly impede innovation entities’ ability to engage in green innovation within a uniform market environment, making it challenging for the market to effectively stimulate “demand-induced innovation” [54,55]. Presently, there is an issue with China’s provincial and municipal governments’ regulation of factor markets. This market segmentation phenomenon helps regional governments rationally mobilize internal resources and drive short-term economic growth. However, it is not conducive to long-term sustainable innovation development and may affect the spatial spillover of demand factors on green innovation. Given this context, the following research hypotheses are proposed:

H3a: *Demand factors exhibit spatial spillover effects in influencing green innovation.*

H3b: *The degree of market segmentation moderates the spatial spillover effects of demand factors in influencing green innovation.*

3. Methods and Materials

3.1. Model and Variables

Griliches [56] proposed a knowledge production function to describe the relationship between the factors of knowledge production and innovation output, building upon the Cobb–Douglas production function. It can be expressed by the following formula:

$$Y = AK^{\alpha}L^{\beta} \quad (1)$$

Here, Y represents the level of knowledge output, and K and L are the factors of production in innovation activities, while A represents other factors influencing innovation. The influence of heteroscedasticity can be eliminated by calculating the natural logarithm of both sides of the aforementioned equation, yielding the following result:

$$\ln Y = \alpha \ln K + \beta \ln L + C + u \quad (2)$$

The empirical model presented in this research builds upon the previously established model to investigate the influence of demand factors on green innovation. It presents variables for the level of demand in the home country, the level of demand abroad, the demand structure, and pertinent control factors. Following the modeling approach of panel data models [10] and after data preprocessing and Hausman tests, the following panel fixed-effects baseline regression model is constructed:

$$\ln Innovation_{it} = \alpha_1 \ln Internal_{it} + \alpha_2 \ln External_{it} + \alpha_3 Gap_{it} + \lambda \ln X_{it} + \alpha_0 + \mu_i + v_t + \varepsilon_{it} \quad (3)$$

where $\ln Innovation_{it}$ represents the level of green innovation. $\ln Internal_{it}$ corresponds to the domestic demand factor within the demand level. $\ln External_{it}$ represents the foreign demand factor within the demand level. Gap_{it} is the demand structure variable. $\ln X_{it}$ denotes the control variables. α and λ are the estimated parameters, and μ_i and v_t are individual and time fixed effects, respectively. ε_{it} is a random disturbance term. The year is denoted by t , while the regions are represented by i .

This section provides a description of the explanatory variable, “green innovation level”, and the core explanatory variables, “domestic demand level”, “foreign demand level”, and “domestic demand structure”. Additionally, it explains the selection and measurement of the remaining control variables.

3.1.1. Dependent Variable

Green innovation (patent): A strong indicator of green innovation is the volume of green innovation patent applications filed annually in the sample cities. Previous empirical research has often measured the level of innovation using metrics such as the number of patents or sales of novel products. The authors chose to use data on green patent applications to quantify the level of green innovation, given the research topic and data availability. There are two main reasons for this choice: First, compared to other data sources, green patent data can better capture green innovation activities without being influenced by input factors. Secondly, given the nature and characteristics of green patent output, where the duration of different patent grants varies and is associated with numerous complex factors, the use of green patent application data instead of granted patent data can provide a more accurate and timely reflection of the state of green innovation.

3.1.2. Independent Variable

Domestic demand (income): Per capita disposable income is used to calculate domestic demand. Survey data have been used extensively in prior research to quantify market demand. This study employs the per capita disposable income of the population as a representative demand variable from a macroeconomic point of view. In China, household final consumption constitutes the majority of domestic demand, with the government accounting for a very tiny portion of the total. In turn, household consumption is determined by disposable income per capita. As a result, it makes sense to gauge domestic demand using per capita disposable income. In particular, the average disposable income per person is calculated by taking a weighted average of the disposable incomes of both urban and rural areas. The corresponding percentages of the urban and rural populations in the city are used as the weights.

Foreign demand (export): The sum of all regional exports is used to gauge foreign demand. Businesses can only satisfy the demands of overseas markets by expanding the number of cutting-edge items they export that adhere to global environmental standards. The number of new product exports can influence local businesses’ innovative behavior in green production through foreign markets and serve as a gauge of their capacity for innovation and the level of international competitiveness. Furthermore, a key metric for assessing the competitiveness and growth of the area’s economy is the total value of products exported. It displays the degree of trade and communication between the area

and other nations or areas. As a result, this study used regional export totals to gauge foreign demand from international marketplaces.

Demand Structure (theil index): Many scholars have examined the innovation and demand structure from the perspective of economic inequality [14,57]. The existence of income gaps indicates variations in the distribution of income, which suggests that consumers within the market have varying income levels. The market's demand structure is formed by the various consumer income levels that may be divided into discrete consumer groups, each of which has unique preferences. Therefore, the purpose of this study is to use income distribution to describe the demand structure. The authors of this study chose the Theil index as a stand-in variable for income distribution in light of relevant issues and practical data availability. The inclusion of indicators accounting for both urban and rural populations makes the Theil index a more realistic depiction than traditional measurements, such as income ratios. The specific formula for its calculation is as follows:

$$theil\ index_{it} = \sum_{j=1}^2 (y_{ijt}) \ln \frac{y_{ijt}}{x_{ijt}} \quad (4)$$

Among these, i denotes cities, $j = 1, 2$ distinguishes between urban and rural areas, t signifies the year, x_{ijt} signifies the proportion of the urban or rural population of city i in year t relative to the total city population, and y_{ijt} signifies the proportion of the urban or rural residents' income in city i in year t relative to the total provincial income.

3.1.3. Control Variables

1. **Regional industrial structure (si):** The value contributed by the secondary industry in an area serves as a proxy for the industrial structure of that region. An area may be more accountable for pollution management and environmental protection if its industrial structure is mostly manufacturing-oriented, which is good for the growth of green innovation [58].
2. **Population (pop):** The number of people who live there permanently is used to calculate the size of the population. In terms of education, investment, and innovation endowments, China's cities with varying populations differ significantly from one another. Controlling for the number of permanent inhabitants is crucial because this can have an impact on green innovation.
3. **Government influence on innovation (techr):** The ratio of government spending on technology to fiscal spending serves as a proxy for government influence on innovation. Government influence on the development of green products is important, according to Horbach's research [16], so this must be taken into account as a control variable.
4. **Educational attainment of residents (edur):** The ratio of education spending to fiscal expenditure indicates the inhabitants' degree of educational attainment. An essential measure of a nation's or region's degree of progress is its level of education. People with higher education levels are generally more open to new ideas, which helps drive up demand for green innovations and ensures their ongoing spread [59].
5. **Degree of foreign openness (fdir):** The ratio of foreign direct investment (FDI) to gross domestic product (GDP) per capita is used to quantify the degree of foreign openness. Greater levels of openness to international investment are likely to draw in foreign companies with more stringent environmental regulations to the local market, which will help green innovation flourish in the area. On the other hand, emerging nations could prioritize environmental preservation and green innovation less than wealthy nations and areas. A "pollution haven" effect might result from the entry of foreign businesses in these situations, which would be harmful to green innovation [10]. Details of all variables are shown in Table 1.

Table 1. Variable measurements.

Variable Types	Variables	Symbols	Measure
Dependent variable	Green innovation	patent	Number of granted green patents
Independent variables	Domestic demand	income	Per capita disposable income
	Foreign demand	export	Total export volume
	Demand structure	theil index	Theil index
	Regional industrial structure	si	The added value of the secondary industry
Control variables	Population	pop	The number of permanent residents in the city
	Government influence on innovation	techr	The proportion of technology expenditure to fiscal expenditure
	Educational attainment of residents	edur	The proportion of education expenditure to fiscal expenditure
	Degree of foreign openness	fdir	The proportion of FDI to per capita GDP

3.2. Data Sources

Information on green patents in the data used in this study was identified based on the “IPC Green Inventory” from the World Intellectual Property Organization. In the context of our research, we utilized the search platform Patsnap to identify patents listed within the WIPO “IPC Green Inventory” List. Once identified, these patents were matched to their respective cities according to the applicant’s address information. Data for 261 Chinese cities from 2008 to 2020 were selected for this study because of the availability of data for cities at the prefecture level. With the exception of patent data, data for each city for the remaining research variables were sourced from economic bulletins, various city statistical yearbooks, and the China City Statistical Yearbook. All relevant variables were based on 2008 as the base year, with adjustments made using the consumer price index to remove price-related factors. In addition, to address the potential problem of heteroscedasticity in the model, logarithmic transformations were applied to all non-ratio variables. For descriptive statistics of the variables and a complete list of hyperlinks to the above data sources, see Appendix A.

4. Research Results

4.1. Baseline Regression

To ensure that panel data are stationary and avoid spurious regression issues, this study conducted unit root tests on the panel data before performing the baseline regression. These tests were carried out to examine whether the variables exhibit the same order of integration. Three methods, namely the LLC test, IPS test, and ADF test, were applied to subject the variables to unit root testing. The results of these tests demonstrate that all variables are stationary at level. Detailed test results can be found in Appendix A.

To assess the effects of demand factors on green innovation, based on the results of the Hausman test, this study initially conducted a regression estimation using a panel fixed effects model specified in Equation (1), employing data from 261 Chinese cities spanning the period from 2008 to 2020. Table 2 presents the findings of the regression estimates. Column (1) displays results without the addition of control variables, while Column (2) shows results with the inclusion of control variables. Notably, both Column (1) and Column (2) account for the effects of time-fixed and city-fixed factors.

From the regression results, it is evident that demand factors have a significant impact on green innovation, whether or not control variables are included. Taking Column (2) as an example, it is evident that the regression coefficient for domestic demand (income) is 0.534 at the 1% level, demonstrating high significance. Thus, for every unit increase in domestic demand, the number of green innovation patents increases by 0.534%. Second, the regression coefficient for foreign demand related to exports is significant at the 1% level and estimated at 0.088. Thus, for every unit increase in foreign demand, green innovation increases by 0.088%. The importance of demand-driven contributions to the promotion of green innovation in China is highlighted by these findings. Moreover, it is clear that the rise

in domestic demand stimulates green innovation more strongly than the rise in overseas demand. This aligns with the research perspectives of J. Chen et al. and Sanni [10,60], and this is possibly due to China's global leadership in the size of its domestic consumer market, making the impact of domestic demand more direct. Lastly, the regression coefficient for the demand structure (theil index) is -2.506 . This implies that for each unit increase in the irrationality of the demand structure, the number of green innovation patents decreases by 2.506%. In other words, an increase in income inequality inhibits the development of green innovation. The reason behind this might perhaps be attributed to an irrational demand structure, which diminishes the prospective market size for green innovation items. This, in turn, impacts corporate motivation for green innovation and impedes its creation and advancement. The above results align with Hypotheses H1a, H1b, and H1c proposed in this paper.

Table 2. Baseline regression.

Variable	(1)	(2)
income	0.639 *** (0.17)	0.534 *** (0.16)
export	0.109 *** (0.02)	0.088 *** (0.02)
theil index	-2.078 ** (0.90)	-2.506 *** (0.92)
Control variable	NO	YES
Time fixed effect	YES	YES
City fixed effect	YES	YES
Observations	3393	3393
R-squared	0.838	0.848

Notes: ***, ** are significance levels of 1%, 5%, respectively. Standard errors are in brackets.

4.2. Robustness Test

4.2.1. Robustness Tests

This study aimed to analyze the findings through five techniques to ensure the stability of the regression results. The outcomes are presented in Table 3.

Table 3. Robustness tests.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
income	0.706 *** (0.12)	0.609 *** (0.16)	0.549 *** (0.16)	1.268 *** (0.20)	0.706 *** (0.17)	0.138 ** (0.04)
export	0.077 *** (0.01)	0.088 *** (0.02)	0.088 *** (0.02)	0.094 *** (0.02)	0.089 *** (0.02)	0.028 *** (0.01)
theil index	-2.085 *** (0.25)		-2.565 ** (1.02)	-2.984 *** (0.89)	-2.676 *** (0.87)	-1.276 *** (0.17)
ratio		-0.224 *** (0.07)				
Control variable	YES	YES	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES	YES	YES
Observations	3393	3393	3341	3393	3393	3393
R-squared	0.859	0.848	0.846	0.838	0.849	0.143

Notes: ***, ** are significance levels of 1%, 5%, respectively. Standard errors are in brackets.

Replacement of the dependent variable: This method replaces the count of green patent applications with the count of granted green patents, providing insight into the level of green innovation. After the replacement, the regression analysis results for the full sample in the first column show that the regression coefficients for domestic demand

and foreign demand are significantly positive, while the demand structure variable is significantly negative, which is in line with the results of the baseline regression.

Substitution of the core explanatory variable: In this method, the Theil index, representing the demand structure, is replaced by the urban–rural income ratio. The regression results in the second column show that the regression coefficients for domestic and foreign demand are significantly positive, while the urban–rural income ratio variable is significantly negative, consistent with the baseline regression results.

Excluding direct-controlled municipalities: In China, cities with higher administrative levels have more resources and greater resource allocation rights than other cities [61]. This study conducted robustness tests by excluding these municipalities. The results in the third column show that the regression coefficients for domestic and foreign demand are significantly positive, while the demand structure coefficient is significantly negative, consistent with the baseline regression results.

Sample truncation test: To address potential issues of extreme values in the variables affecting the robustness of the regression results, this study conducted a two-sided sample truncation at the 1st and 5th percentiles. The results in the fourth and fifth columns, after conducting the two-tailed truncation test at the 1% and 5% percentiles, show that the coefficients for domestic and foreign demand are significantly positive, while the demand structure coefficient is significantly negative. So, the results are robust.

Robustness test for negative binomial regression: In addition, this study conducted a robustness test using negative binomial regression, which is commonly used in count data regression. The results in the sixth column indicate that the baseline results are robust.

4.2.2. Endogeneity Issues

In the context of this analysis, causal relationships between variables may lead to endogeneity issues, meaning that green innovation may, in turn, affect demand factors. In order to address potential endogeneity and omitted-variable issues, two-stage least squares (2SLS) were used to regress the sample. Since instrumental variables must be related to the explanatory variables but unrelated to the error term, two categories of instrumental variables were selected for regression. First, lagged one-period domestic and foreign demand variables were used in the regression. Second, the third moment of the explanatory variables, i.e., the $(x_i - \bar{x})^3$ statistic, was used as an instrumental variable in the regression. Table 4 shows the findings.

Table 4. Endogeneity test.

Variable	(1)	(2)
income	0.571 ** (0.24)	0.468 *** (0.16)
export	0.135 *** (0.03)	0.084 *** (0.02)
theil index	−2.170 *** (0.63)	−3.202 *** (0.82)
Control variable	YES	YES
Time fixed effect	YES	YES
City fixed effect	YES	YES
Observations	3132	3393
R-squared	0.955	0.953

Notes: ***, ** are significance levels of 1%, 5%, respectively. Standard errors are in brackets.

According to the regression results, there is a substantial positive relationship between the regression coefficients of domestic and overseas demand for green innovation. It implies that a boost of green innovation is facilitated by increased demand. Conversely, the regression coefficient for the demand structure is significantly negative, suggesting that an inappropriate demand structure may inhibit the development of green innovation to some extent. These results show that the research conclusions, after addressing endogeneity

issues, are consistent with the baseline regression, indicating a certain degree of reliability in the findings of this study.

4.3. Heterogeneity Analysis

Patent-type heterogeneity: Building on the research by Horbach et al., who categorized green innovation based on its varying environmental impacts, such as materials, energy, and air pollution [11], and identified 12 different types of green innovation, this study assessed the effects of “demand factors” on these distinct types of green innovation. Similarly, Demirel and Kesidou conducted research using a comparable approach [17] and found that different types of green innovation are influenced by different determining factors. This study investigated patent-type heterogeneity in the demand-pull effect using this research approach, based on the category concept of green innovation patents in China, invention patents, and utility model patents. To determine whether demand variables have varying impacts on invention patents and green utility model patents, which are the two categories that all sampled green patents are categorized into, we specifically examined this. The details are presented in Table 5.

Table 5. Patent-type heterogeneity.

Variable	Invention Patents	Utility Model Patents
income	0.431 * (0.22)	0.765 *** (0.07)
export	0.085 *** (0.03)	0.078 *** (0.01)
theil index	−2.922 ** (1.14)	−1.818 *** (0.40)
Control variable	YES	YES
Time fixed effect	YES	YES
City fixed effect	YES	YES
Observations	3393	3393
R-squared	0.716	0.857

Notes: ***, **, and * are significance levels of 1%, 5%, and 10%, respectively. Standard errors are in brackets.

According to the findings, both types of patents receive a considerable boost from increased domestic demand, with utility patents benefiting more than invention-type patents. The rising domestic demand, reflecting higher income levels, leads to a desire for an improved quality of life, driving businesses to engage in green innovation to meet consumer demands. In the short term, green utility model patents are more responsive, as they involve improvements to existing technologies, making them better suited to promptly meet market needs. Additionally, the rise in foreign demand benefits both green invention patents and green utility model patents, with a slightly greater impact on the former. This is likely due to the fact that green invention patents typically involve creating new technologies with longer research and development cycles, thus making foreign demand, particularly in technological cooperation, more significant. Lastly, the regression coefficients for the demand structure are significantly negative in both cases, indicating a negative influence on both types of green innovation. The effect is more pronounced on green invention patents. This may be associated with an increase in income disparities, leading to a reduction in the market share of green innovation. This aligns with Hypothesis H2a in this paper.

Regional heterogeneity: Considering the significant variations in economic development and innovation potential across different regions in China, it is crucial to further analyze whether there is regional heterogeneity in the impact of demand factors on green innovation [62]. This paper divides all sampled cities into two major regions: the eastern and central–western regions. Table 6 displays the specific estimation outcomes and investigates the influence of demand drivers on green innovation in these different regions.

Table 6. Regional heterogeneity.

Variable	Eastern Region	Central–Western Region
income	0.854 *** (0.15)	−0.121 (0.20)
export	0.066 (0.05)	0.069 ** (0.02)
theil index	−3.510 *** (0.61)	−1.256 (1.35)
Control variable	YES	YES
Time fixed effect	YES	YES
City fixed effect	YES	YES
Observations	1521	1872
R-squared	0.839	0.860

Notes: ***, ** is significance levels of 1%, 5%, respectively. Standard errors are in brackets.

Based on the results, in the eastern region, an increase in income levels significantly promotes green innovation, while an increase in income disparity exhibits a significant inhibitory effect. As income levels rise, there is an increasing demand for green innovation items in the eastern region due to its greater development and higher levels of environmental awareness among its residents compared to the central and western regions. Conversely, a widening income disparity in the east significantly hinders green innovation, possibly due to the reduced market demand caused by the growing income gap. In the central and western regions, changes in income levels and income disparities do not significantly affect green innovation. However, an increase in export volume will have a promoting effect. This might be attributed to the relatively low income levels among residents in these regions and a relatively weak environmental awareness, making them more sensitive to the environmental attributes of products concerning their prices. Therefore, changes in domestic demand factors have a limited impact on green innovation. Additionally, the central and western regions are more reliant on traditional resource-based industries. When residents' income rises, it may be associated with the development of traditional industries, but it does not significantly contribute to green innovation. In contrast to domestic demand factors, foreign demand factors in these regions potentially lead to green innovation progress due to their geographic location. The western region, in particular, possesses abundant natural resources, and the development of these resources can stimulate the innovation of green technologies, meeting the foreign market's demand for clean-energy products. These findings confirm Hypothesis H2b proposed in this study.

5. Further Exploration of Spatial Effects

Some studies have found that green innovation exhibits spatial spillover effects [5,19]. Therefore, building upon the baseline regression, this study employed spatial econometric models to analyze the spatial spillover effects of demand factors on green innovation levels. Given that the spatial Durbin model considers both spatial lag in the dependent variable and spatially autocorrelated error terms, this study opted for the Spatial Panel Durbin Model for estimation. Taking into account the factors mentioned above and building upon the study by Duan and Xia [58], in order to identify the demand spillover effects, this research used the Spatial Panel Durbin Model. Equation (5) provides the specific formulation of the model:

$$\begin{aligned}
 Patent_{it} = & \alpha_0 + \rho W_{ij} patent_{it} + \alpha_1 income_{it} + \alpha_2 export_{it} + \alpha_3 theil\ index_{it} + \lambda X_{it} \\
 & + \delta_1 W_{ij} income_{it} + \delta_2 W_{ij} export_{it} + \delta_3 W_{ij} theil\ index_{it} + \delta_4 W_{ij} X_{it} + \mu_i + v_i + \varepsilon_{it}
 \end{aligned} \quad (5)$$

In the specified model, $Patient_{it}$ represents the level of green innovation at time t for entity i . $income_{it}$ corresponds to the internal demand factor, namely, the income level, at time t . $export_{it}$ signifies the external demand factor, specifically the total exports, at time t . $theilindex_{it}$ stands for the Theil index, which represents the demand structure,

at time t . X_{ij} represents the vector of control variables. u_i represents the individual fixed effects, capturing unobserved heterogeneity across entities. v_t represents the time fixed effects, accounting for common time-related effects. ε_i symbolizes the independently and identically distributed random disturbances, satisfying $\mu_{it} \sim \text{idd}(0, \sigma^2)$ and $\varepsilon_{it} \sim \text{idd}(0, \sigma^2)$. W_{ij} stands for the spatial weight matrix, representing spatial interactions or relationships between entities i and j .

In this study, two distinct spatial weight matrices were employed. Firstly, a spatial inverse distance matrix W_{1ij} was constructed using geographical distances as the criterion:

$$W_{1ij} = \begin{cases} \frac{1}{d_{ij}^2}, & i \neq j \\ 0, & i = j \end{cases} \quad (6)$$

In this context, d represents the straight-line distance between the geographical centers of two regions.

This study also drew inspiration from the research conducted by Li [63] and established an economic matrix W_{2ij} with the following expression:

$$W_{2ij} = W_{1ij} \times \text{diag}\left(\frac{\bar{Y}_1}{\bar{Y}}, \frac{\bar{Y}_2}{\bar{Y}}, \dots, \frac{\bar{Y}_N}{\bar{Y}}\right) \quad (7)$$

In the provided equation, W_{1ij} refers to the spatial inverse distance matrix. $Y_i = 1 / (t_1 - t_0 + 1) \sum_{t=t_0}^{t_1} Y_{it}$ is the average per capita gross domestic product (GDP) of region i at the observed time. $\bar{Y} = \frac{1}{n(t_1 - t_0 + 1)} \sum_{i=1}^n \sum_{t=t_0}^{t_1} Y_{it}$ denotes the average total GDP during the observed period, and t represents different time periods.

Both of the aforementioned spatial weight matrices have been normalized by rows to eliminate the influence of data dimensionality. This approach ensures that the spatial interactions and their effects are captured effectively while accounting for the economic dynamics of the regions under investigation.

Before conducting spatial panel regression analysis, it is necessary to perform the relevant statistical tests. The first test is to examine whether there is a spatial correlation among the primary variables across different regions. After conducting the test, it was confirmed that spatial econometric models are appropriate for regression in this study. The spatial Durbin model was identified as the optimal choice. Appendix A has a detailed presentation of the test. As in the research conducted by LeSage and Pace [64], when the spatial term coefficient ρ in the model estimation results is not zero, it indicates the presence of spatial interactions between neighboring regions. Using only regression coefficients to explain spatial regression results can lead to biases. The parameter estimates of a spatial Durbin model do not directly reflect the true effects of direct effects and spatial spillover effects. The results need to be decomposed into direct effects, indirect effects, and total effects [64]. The study presents the effects of local independent factors on local green innovation through their direct impacts. Spatial spillover effects, commonly known as indirect impacts, result from independent factors in neighboring regions influencing local green innovation. The combined value of direct and indirect impacts is referred to as total effects. Since those objects of spatial spillover effects are within China's borders, the discussion of foreign demand factors, represented by total exports, is not included in the subsequent spatial econometric analysis. The results of the spatial econometric model are presented in Table 7.

Table 7. Effect decomposition of the dynamic SDM.

Variable	W ₁			W ₂		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
income	0.555 *** (0.12)	−0.891 ** (0.42)	−0.336 (0.41)	0.576 *** (0.11)	−1.064 ** (0.42)	−0.488 (0.41)
theil index	−1.986 *** (0.44)	−3.329 * (1.73)	−5.315 *** (1.81)	−2.031 *** (0.44)	−3.827 ** (1.72)	−5.858 *** (1.79)
Control variable		YES			YES	
Time fixed effect		YES			YES	
City fixed effect		YES			YES	

Notes: ***, **, and * are significance levels of 1%, 5%, and 10%, respectively. Standard errors are in brackets.

In terms of direct effects, the coefficients for income level and export volume are significantly positive, while the income gap coefficient is significantly negative. This implies that local green innovation is greatly benefited by the rise in domestic demand, which is mostly reflected in income levels. This outcome adheres to the idea of “demand-driven innovation”, which holds that demand is the main force behind green innovation. On the other hand, the widening income gap moderately inhibits local green innovation. This may be due to increased income inequality, leading to a reduction in the market size for green innovation products. Additionally, when comparing the direct effects obtained from the spatial panel model with the results of the basic regression that did not include spatial factors, the conclusions are consistent.

Regarding the indirect effects, the coefficient for income level is significantly negative, and the income gap coefficient is also significantly negative. This implies that changes in the demand levels of neighboring areas will exert a “siphoning effect” on local green innovation. Given the relatively high costs associated with green innovation, market demand levels are a critical factor considered by innovators. An increase in demand from neighboring areas attracts more green innovation elements, thereby promoting local green innovation. The impact of an irrational demand structure on green innovation also spills over from the local area to adjacent regions. An increase in the income gap in adjacent regions enhances the willingness of the high-income class to pay for innovative products, thereby increasing effective demand in adjacent areas. This encourages local green innovation to relocate to neighboring areas to gain more demand support, ultimately inhibiting local green innovation. It is worth noting that under the economic matrix condition, all coefficients are larger than when using a geographic distance matrix, indicating that spatial spillover is more pronounced among cities with similar levels of economic development. The findings above confirm Hypothesis H3a.

Previous research indicates that demand factors influencing green innovation could cause spatial spillover effects. Nonetheless, if local governments decide to implement regional protection strategies by artificially increasing the market entry barriers, it may lead to higher cross-regional circulation costs for various factors. Innovators may encounter challenges in carrying out innovative activities within a market demand environment that is not uniform, thereby hampering the market’s function of promoting “demand-induced innovation” [65]. Currently, China’s economic landscape is characterized by the problem of factor market regulation by provincial and municipal governments, and market segmentation is a fact. This regulation, to some extent, helps local governments mobilize internal resources and advance short-term economic growth. Nevertheless, it does not support the sustainable development of innovation in the long term. Next, this paper will approach the issue objectively, introducing market segmentation variables and utilizing interaction terms for the empirical analysis of potential spatial moderating effects of market segmentation levels on the influence of demand factors on green innovation development.

We build upon the market segmentation calculation framework introduced by Parsley and Wei [66]. It establishes a three-dimensional panel dataset encompassing time, regions, and product categories. To provide a more precise assessment of market segmentation

across regions, the analysis focuses on consumer price indices (CPIs) for seven major commodity categories obtained from statistical yearbooks of various sample cities spanning the years 2008 to 2020. These categories encompass Food, Tobacco, and Alcohol; Clothing; Articles for Daily Use and Services; Health Care; Transportation and Communication; Residence; and Education, Culture, and Recreation. This methodological approach is designed to enhance the accuracy and reliability of our analysis, enabling a more comprehensive evaluation of market segmentation dynamics among different regions. See Appendix B for details.

The regression results after introducing market segmentation are shown in Table 8.

Table 8. Moderating effect of market segmentation.

Variable	W ₁			W ₂		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
income × seg	0.391 (0.62)	−8.542 *** (3.03)	−8.152 ** (3.18)	0.435 (0.62)	−6.888 *** (2.60)	−6.453 ** (2.77)
theilindex × seg	−11.619 ** (4.71)	−82.805 *** (25.4)	−94.424 *** (25.94)	−12.142 *** (4.72)	−63.193 ** (25.19)	−75.336 *** (25.78)
seg	−0.982 (5.43)	114.330 *** (27.7)	113.348 *** (29.08)	0.655 (0.46)	94.573 *** (25.5)	93.918 *** (26.92)
income	0.515 *** (0.12)	−0.598 (0.412)	−0.083 (0.40)	0.545 *** (0.12)	−0.748 * (0.41)	−0.203 (0.40)
theil index	−1.190 ** (0.53)	1.753 (2.23)	0.563 (2.28)	−1.189** (5.46)	0.189 (2.22)	−1.001 (2.27)
Control variable		YES			YES	
Time fixed effect		YES			YES	
City fixed effect		YES			YES	

Notes: ***, **, and * are significance levels of 1%, 5%, and 10%, respectively. Standard errors are in brackets.

The results in Table 8 indicate that upon introducing the interaction terms *income* × *seg* and *theilindex* × *seg*, the indirect effect coefficients of market segmentation in relation to income level and income disparity are both negative and statistically significant. However, the direct effect of the interaction term is not statistically significant. This suggests that as market segmentation increases, the synergistic effect of income level on the neighboring regions' green innovation becomes more pronounced, simultaneously intensifying the suppressive impact of an unreasonable demand structure on green innovation development in adjacent areas. This validates Hypothesis H3b. Thus, it follows that market segmentation has a detrimental effect on green innovation. This may be explained by the increasing degree of market segmentation, which raises barriers to entry for various geographic areas. As a result, expanding the scale of effective demand becomes challenging, ultimately hindering the inherent impetus for innovation. This situation is unfavorable for the progression of various forms of green innovation activities.

6. Discussion

This study examines the impact of demand factors on green innovation from three perspectives: domestic demand level, foreign demand level, and domestic demand structure. The empirical results based on Chinese city-level data confirm a positive association between increased demand levels and the development of green innovation, aligning with Hypotheses H1a and H1b proposed in this paper. Notably, it is not solely the magnitude of demand levels that matters; the research findings also reveal that an expanding income gap can impede green innovation. In contrast to previous studies that suggest negative implications of income inequality on technological innovation [67,68], this research underscores how income inequality may, in fact, act as an inhibitor of green innovation. This phenomenon may stem from an imbalance in demand structures, which reduces the market size for green innovation products, thereby impacting the emergence of green innovation.

Furthermore, the study's results indicate that demand factors exert heterogeneous influences on green innovation across different regions and patent types, validating Hypotheses H2a and H2b. Horbach et al. [11], in their research, categorized environmentally friendly innovations based on their varying environmental impacts and found differing levels of influence on different types of patents. This paper, employing data at the city level in China, in line with China's patent categorization, distinguishes between invention patents and utility model patents within green innovation and reaches similar conclusions. Such heterogeneity offers valuable insights to policymakers, emphasizing the need for tailored, context-specific environmental policies that consider the requirements of different regions and patent types.

Finally, further analysis in this study demonstrates the presence of spatial spillover effects on the influence of demand factors on green innovation. This not only validates the last hypothesis, H3, but also aligns with the findings of Shao et al. [5]. Additionally, leveraging the advantage of using city-level data, this paper delves into market segmentation and reveals that intensified market segmentation has a detrimental impact on the spatial spillover of the demand's influence on green innovation. This provides an intriguing perspective for a comprehensive understanding of the spatial spillover effects of demand.

7. Conclusions

7.1. Conclusions

This study conducted empirical studies using a dataset that included 261 cities that were at the prefecture level or higher between 2008 and 2020 in China. The study utilized econometric techniques, including panel data models and spatial Durbin models, to examine the influence of demand determinants on green innovation. Additionally, spatial spillover effects and the moderating impact of market segmentation on demand-induced effects in the context of green innovation were investigated. The following are the study's major findings: First, green innovation receives significant benefits from rising levels of domestic as well as overseas demand. Conversely, a widening income gap significantly inhibits the development of green innovation. Second, demand factors exhibit clear heterogeneity in their effects on green innovation, varying by patent type and regional characteristics. After introducing spatial factors, it was discovered that an elevation in demand levels in neighboring regions yields a detrimental spillover impact on local green innovation. Likewise, a rise in income inequality in neighboring regions also results in negative spatial spillover. The influence of demand considerations on green innovation is moderated by market segmentation. The more segmented the market is, the greater the "siphoning" effect when demand increases in nearby areas. Moreover, an unsuitable demand structure in neighboring regions exacerbates the hindering effect on local green innovation development. These results offer valuable perspectives on the varied impacts of demand-related factors on green innovation in China.

7.2. Implications

Based on the empirical findings presented in this paper, several policy implications can be derived. Firstly, our research findings underscore the importance of demand as a significant factor influencing the development of green innovation. Therefore, proactive measures should be taken to cultivate domestic and international demand markets. This includes continuously increasing disposable income for residents, enhancing their capacity to consume green innovation products, and leveraging domestic demand to drive green innovation. Additionally, it is essential to maintain a high level of international openness, actively introduce advanced international green technologies, and strengthen the protection of intellectual property rights related to international green technologies to stimulate foreign demand for green innovation. Furthermore, region-specific innovation policies tailored to local conditions should be established to promote green innovation. Our study reveals that demand factors have different impacts on green innovation in various regions. As a result, addressing disparities in green innovation among regions and exploring strategies

for green innovation development in underdeveloped areas are crucial for enhancing green innovation efficiency. Lastly, expediting the development of unified factor markets is vital. This involves removing market fragmentation in domestic factor markets and establishing unified markets that allow for the free flow of factors. This, in turn, will significantly enhance the role of demand in driving green innovation development.

7.3. Limitations and Outlooks

Using econometric models, this research examines how demand factors affect green innovation. However, some limitations arising from the research conditions and perspectives require additional investigation. Firstly, we centered our study on Chinese prefecture-level cities, which provides a more detailed research scale. Nevertheless, given that there are about 300 such cities in China, we could not include all cities in our study due to data constraints. The unavailability of data limited the study's ability to thoroughly examine some cities in the western regions. Improving data accessibility should be the main goal of future research. Using China as an illustrative example, this study also examined how demand factors influence green innovation in that country. However, due to the various economic, social, and innovative landscapes across different countries worldwide, further research could extend beyond China to offer valuable insights into driving green innovation on a big scale.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The link to the detailed classification of green patents provided by WIPO is <https://www.wipo.int/classifications/ipc/green-inventory/home> (accessed on 1 August 2023). The link to the platform for conducting patent retrieval and analysis, Patsnap, is <https://www.zhiihuiya.com/analytics> (accessed on 1 August 2023). The link to the China Statistical Yearbook can be found at <http://www.stats.gov.cn/sj/ndsj/> (accessed on 1 August 2023). The link to find statistical yearbooks or statistical bulletins of various provinces or cities in China, along with additional information, can be located at the website <http://www.stats.gov.cn/> (accessed on 1 August 2023).

Table A1. Descriptive statistics of variables.

Variable	Observation Number	Mean	Deviation	Minimum	Maximum
patent	3393	4.834	1.711	0.000	10.466
income	3393	9.653	0.430	8.233	10.901
export	3393	17.948	2.000	8.894	23.267
theil index	3393	0.084	0.047	0.004	0.355
fdir	3393	0.006	0.008	0.000	0.110
edur	3393	0.180	0.042	0.010	0.377
techr	3393	0.016	0.016	0.001	0.207
si	3393	0.473	0.104	0.000	0.851
pop	3393	5.941	0.639	3.877	8.074

Table A2. The results of stationarity tests.

Variable	LLC	IPS	ADF
patent	−18.066 ***	−14.017 ***	819.204 ***
income	−18.222 ***	−11.448 ***	827.331 ***
export	−18.493 ***	−9.474 ***	727.439 ***
theil index	−20.601 ***	−12.408 ***	855.854 ***
fdir	−39.295 ***	−13.104 ***	1330.7538 ***
edur	−21.859 ***	−16.108 ***	883.421 ***
techr	−11.946 ***	−9.589 ***	695.806 ***
si	−16.004 ***	−3.639 ***	672.973 ***
pop	−72.703 ***	−2.454 ***	2963.740 ***

Notes: ***, $p < 0.01$.**Table A3.** Spatial correlation test results for the explained variable.

Year	W ₁			W ₂		
	Moran's I	Z Value	p Value	Moran's I	Z Value	p Value
2008	0.208	8.271	0.000	0.209	8.058	0.000
2009	0.233	9.235	0.000	0.223	8.597	0.000
2010	0.242	9.571	0.000	0.238	9.153	0.000
2011	0.257	10.150	0.000	0.256	9.851	0.000
2012	0.248	9.820	0.000	0.247	9.531	0.000
2013	0.245	9.692	0.000	0.244	9.387	0.000
2014	0.257	10.174	0.000	0.251	9.677	0.000
2015	0.300	11.849	0.000	0.297	11.422	0.000
2016	0.307	12.112	0.000	0.301	11.574	0.000
2017	0.313	12.361	0.000	0.310	11.894	0.000
2018	0.335	13.200	0.000	0.329	12.630	0.000
2019	0.315	12.434	0.000	0.307	11.810	0.000
2020	0.316	12.466	0.000	0.310	11.905	0.000

Table A4. Spatial model selection.

Methods	W ₁	W ₂
LM-spatial lag	259.891 (0.000)	254.057 (0.000)
Robust LM-spatial lag	84.698 (0.000)	79.63 (0.000)
LM-spatial error	425.054 (0.000)	419.576 (0.000)
Robust LM-spatial error	249.861 (0.000)	245.193 (0.000)
Wald-spatial lag	40.79 (0.000)	36.21 (0.000)
LR-spatial lag	40.82 (0.000)	36.43 (0.000)
Wald-spatial error	64.23 (0.000)	56.51 (0.000)
LR-spatial error	64.56 (0.000)	56.08 (0.000)

Notes: p values in brackets.

Appendix B

When measuring the degree of market segmentation, we begin by employing the logarithm of price ratios in the form of first-order differences. This approach allows us to quantify relative price changes accurately. See Equation (A1) for details.

$$\Delta Q_{ijt}^k = \ln(p_{it}^k / p_{jt}^k) - \ln(p_{it-1}^k / p_{jt-1}^k) = \ln(p_{it}^k / p_{it-1}^k) - \ln(p_{jt}^k / p_{jt-1}^k) \quad (\text{A1})$$

Continuing from the previous point, by taking the absolute values of the relative prices, we aim to mitigate the influence of differing regional position orders on the variance of relative prices. This process leads us to Equation (A2):

$$|\Delta Q_{ijt}^k| = |\ln(p_{it}^k / p_{it-1}^k) - \ln(p_{jt}^k / p_{jt-1}^k)| \quad (\text{A2})$$

Next, we address the systematic errors introduced by fixed effects related to specific products, as proposed by Parsley and Wei [66]. We assume $|\Delta Q_{ijt}^k| = a^k + \varepsilon_{ijt}^k$, where a^k represents the price fluctuations attributed to the inherent characteristics of the k product category, and ε_{ijt}^k is related to the economic relationship between the two regions i and j in year t . To eliminate these fixed effects, we take the average of the relative prices $|\Delta Q_{ijt}^k|$ for all city combinations across years and product categories. Subsequently, we subtract these averages from the respective values, effectively neutralizing the fixed effects. See Equation (A3) for details.

$$q_{ijt}^k = \varepsilon_{ijt}^k - \bar{\varepsilon}_{ijt}^k = |\Delta Q_{ijt}^k| - |\overline{\Delta Q_t^k}| \quad (\text{A3})$$

Next, we proceed to compute the variance of relative price fluctuations for the seven product categories between every pair of sample cities, denoted by $\text{var}(q_{ijt}^k)$. Further, we calculate the overall variance of relative price changes for all city combinations from 2008 to 2020. Taking the group-level average, we can determine the degree of market segmentation for each sample city using Equation (A4):

$$\text{var}(q_{nt}^k) = (\sum_{i \neq j} \text{var}(q_{ijt}^k)) / N \quad (\text{A4})$$

where N is the total number of combined provincial and city pairs, and n is the number of regions.

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