Spatio-Temporal Evolution and Driving Mechanism of Green Innovation in China

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Abstract: Sustainable development has become a global consensus, and green innovation is the key to promoting transition to sustainable development. The study on green innovation contributes to develop and implement green innovation policies. This paper investigates the spatio-temporal characteristics and driving mechanism of green innovation 2009–2019 in China from the perspective of economic geography based on a variety of methods such as GIS tools and Geodetector, in two dimensions of green innovation power (GIP) and green innovation growth ability (GIGA). The findings show that (1) The GIP and GIGA in China continue to increase, with obvious decreasing gradient characteristics from eastern to central and western China, extreme polarization, and obvious spatial aggregation, and the high-value regions show a change from coastal and riverine distribution to coastal distribution, with Shandong and Yangtze River Delta as the centers of high-value regions. (2) The power of the 18 driving factors on green innovation varies widely across time, and the 7 factors such as green area in urban completed area and investment in urban environmental infrastructure facilities are super interaction factors. Besides, the 5 variables of innovation input, foreign connection, economic environment, market environment and environmental regulation have different driving forces on green innovation, suggesting that the driving mechanism has changed in different periods. (3) Core factors of GIP were identified as R&D intramural expenditure and R&D personnel equivalent; important factors were identified as 5 factors such as R&D intramural expenditure in high-tech industry and FDI. Core factors of GIGA were identified as R&D intramural expenditure and added value of financial industry; important factors were identified as 4 factors such as R&D intramural expenditure in high-tech industry and GDP. (4) The 31 provinces in China were classified into 4 types of policy areas by BCG model, and proper policy suggestions were put forward. The research methods and conclusions of this paper can provide reference for green innovation policy optimization in China and other countries under similar conditions.

Keywords: green innovation; green technology patent; spatio-temporal evolution; driving mechanism; China

1. Introduction

1.1. Background

Green innovation can be simply understood as an innovative activity to reduce the adverse impact on the environment or enhance the environmental performance. Similar concepts include eco-innovation, environmental innovation and sustainable innovation [1]. As one of the main themes in sustainable development, green innovation is directly connected to affordable and clean energy, industry, innovation and infrastructure, climate action in the sustainable development goals set by the United Nations, and can be considered an important part of the basic science of sustainable development. Currently, with the rapid growth of global population and economy, natural resources and ecosystems are...
seriously affected and environmental problems are becoming increasingly prominent [2], sustainable development has become a universally recognized consensus and challenge around the world [3,4], and green technology innovation is the key to promoting the transition to global sustainable development [5–7]. Therefore, the study of green innovation has gradually emerged as a hot topic for academic discussion, and also a key area for international cooperation and competition. The current research on green innovation is basically conducted based on three main lines: national or regional green innovation system assessment and green innovation policy design at the macro level, product or technology greening improvement and green industry cluster evolution in specific industries at the meso level, and green innovation management and practice of enterprises at the micro level [8], involving different disciplines such as environmental science, engineering, economics, management and geography. Scholars of economic geography focus on the performance of green innovation activities in space. This paper starts with this point to discuss the spatio-temporal characteristics and driving mechanism of green innovation in depth, and further puts forward targeted optimization suggestions.

China is an active practitioner of green innovation, and as the overarching concept guiding the country’s development, the idea of green development was included in the “Scientific Outlook on Development” as early as 2003, followed by including innovation and green as an important part of the “Five Concepts for Development” in 2015. The Chinese government also tries to implement green innovation policies in several ways. Internationally, it has joined international environmental conventions such as the Montreal Protocol and the Stockholm Convention, fulfilled its international responsibilities in environmental governance, and actively engaged in international cooperation. At home, the “12th Five-Year Plan” and the “13th Five-Year Plan” have made energy conservation and emission reduction a priority, and the proportion of the government’s financial expenditure on science and technology for resource and environmental projects has been maintained at about 12–16% all the year round [9]. After years of development, China has made great progress in green development, for example, the share of clean energy increased by 8.9% between 2012 and 2020 [10], carbon emission intensity decreased by 48.1% between 2005 and 2019 [10], and energy consumption per unit of GDP decreased by 60.7% between 2005 and 2019 [11]. However, there also exists some gap at the green development in China when compared with the world average or developed countries, and even within the country, there are also prominent imbalances in green development among regions [12]. Advancing China’s green development through green innovation remains a very important endeavor. Therefore, China can be used as a very suitable case for green innovation research, and the study on it can not only guide its own development of green innovation, but also is of great reference significance for other countries.

1.2. Literature Review

Regional green innovation is a core concern of economic geography scholars, and this paper makes comments on the relevant literature from three areas: index system and measurement methods, spatial scale and spatial effect, and driving factors.

In terms of index system and measurement methods, the academic circles have not yet reached a unified consensus on the understanding of green innovation, and the measurement indexes are still under exploration, except for both single-index system and multi-index system that have been tentatively established so far. The single indicator system mostly measures green innovation by the green technology patent (GTP) amount [13–19], and a few studies also represent it by corporate R&D expenditure on environment [20,21]. The multi-indicator system evaluates it from a combination of innovation input [22–25], innovation output and green environment [22,23], and economic output [24]. A few studies also measure it in terms of green economy, eco-society, technological progress, environmental protection [26] and investment capacity, management capacity, R&D capacity, production capacity, market capacity, environmental management capacity [27], eco-innovation capacity, eco-innovation environment, eco-innovation activities, and eco-innovation per-
formance [28], based on weighted sum method and AHP method. In addition, some scholars have also conducted study from the perspective of green innovation efficiency, and constructed the index system from three areas of innovation input, expected output and unexpected output based on the methods mainly including dynamic DEA mode [29] in data envelopment analysis (DEA), SBM model [30–34], SBM-DDF model [35], super-SBM model [36–39], super-EBM model [40], two-stage SBM model [41], two-stage network DEA model [42], three-stage super-SBM model [43], and three-stage Malmquist model [44].

In terms of spatial scale and spatial effect, the previous studies have investigated the characteristics of green innovation in four scales of country-country, country, economic zone and city cluster. For example, at the international level, Kobryń and Pryjstoff et al. calculated the eco-innovation capability of EU countries, and concluded that Germany, Denmark, Finland, France, Ireland, and Sweden are in the core group of eco-innovation, while Cyprus, Bulgaria, Croatia, Hungary, Malta, and Poland are in the peripheral group [25]. Jo et al. compared the eco-innovation capabilities of 49 countries in Europe and Asia, noting that European countries and some Asian countries such as Japan, Singapore, Korea, China, and Malaysia are stronger in eco-innovation capabilities, while other Asian countries such as Myanmar, Cambodia, Laos, Vietnam, and the Philippines are weaker [28]. Mavi and Mavi et al. analyzed the eco-innovation efficiency of EU countries and concluded that Germany has the highest ranking and Estonia has the lowest ranking [29]. At the national level, Zhou, Yang, and Fu et al. studied the provincial green innovation ability in China and stated that green innovation ability shows a decreasing gradient from eastern to central and western China, with obvious spatial correlation characteristics, and that eastern and central China are the main green innovation spillover regions [14,15,22]. Zhao, Wu, Miao, Lv and Du et al. calculated the provincial green innovation efficiency in China and stated that the green innovation efficiency varies significantly between provinces, with the eastern and western regions having higher efficiency than the central region and the northeastern region having the lowest, and that there is a significant positive spatial correlation [31,32,41–43]. At the economic zone level, Xu et al. studied the green innovation efficiency of 11 provinces and cities in the Yangtze River Economic Delta and concluded that the green innovation efficiency in the downstream region is higher than that in the upstream and midstream regions, and that the midstream region has a strong “late-developing advantage” [37]. Xu et al. studied the green innovation efficiency of 8 economic zones in China and pointed out that the green innovation efficiency is higher in the southern coastal region, northwest region and southwest region [44]. At the city cluster level, Ge et al. argued that the development of green innovation capacity in Yangtze River Delta is uneven, with regions with stronger capacity mainly along the Yangtze River or coastline, while showing some spatial dependence [23]. Zeng et al. concluded that most cities in Yangtze River Delta have high green innovation efficiency and they are spatially clustered [39]. Wang et al. concluded that the green innovation efficiency of Changsha-Zhuzhou-Xiangtan City Group is at a medium level in general, showing clear inter-city gradients [34]. Chen et al. concluded that the green innovation efficiency in the Guangdong-Hong Kong-Macao Greater Bay Area shows an upward trend on the whole with significant inter-city differences [38].

For influencing factors, the established studies have explored the regional or urban green innovation from the two perspectives of single factor and multi-factors. In terms of single factor, the previous papers have discussed the impact of environmental regulation, FDI, taxation system, carbon trading policy, planning policy and land use misallocation on green innovation ability or efficiency. For example, Kesidou et al. stated that environmental regulation during China’s 11th Five-Year Plan have effectively promoted eco-innovation [17], but Li et al. argued that environmental regulation in different regions of eastern, central and western China has both promoting and inhibiting effects [21]. Yang et al. pointed out that there is a U-shaped relationship between environmental regulation and green innovation efficiency in eastern China, while environmental supervision has no significant impact on green innovation efficiency in central and western China [45]. Dai et al. pointed out that FDI promotes green innovation across China and in the eastern
region, but has no effect in the central region and a negative effect in the western region [46]. Liu et al. further stated that there are several structural breakpoints, beyond which the scale effect and composition effect of FDI will increase significantly, while the technology effect will show a significant decrease [18]. Deng et al. pointed out that there is an inverted U-shaped effect of income and environmental taxes on local and neighboring regions’ green technology innovation, and there is a very significant regional heterogeneity [47]. Du et al. argued that carbon trading policies have a significant boosting effect on green innovation in pilot regions and a significant inhibiting effect on neighboring regions [48]. Xu et al. stated that Regional Planning of Yangtze River Delta has a significant stimulating effect on green technology innovation in the region, but there are significant regional differences [49]. Gao et al. pointed out that land resource mismatch hinders green technology innovation in cities [50]. In terms of multi-factors, Zhou et al. pointed out that city size, economic development and R&D efficiency have a positive impact on provincial green innovation ability, while environmental supervision and R&D reaction have a negative impact [14]. Duan et al. pointed out that environmental regulation intensity, technological innovation level, city size, tertiary industry share and environmental quality have a significant positive contribution to the green innovation ability of cities in the Yangtze River Economic Delta [19]. Fan et al. pointed out that per capita GDP, education expenditure, and the share of tertiary industry help improve urban green innovation efficiency, while the share of workers in the tertiary industry, FDI, and total retail sales of consumer goods are of resistance to it [30]. Wang et al. pointed out that economic development has a positive effect on the green innovation efficiency in Changsha-Zhuzhou-Xiangtan City Group, while education level and industrial structure have a negative effect, and government support and infrastructure level have no effect [34]. Zeng et al. suggested that the expenditure on science and technology and education and per capita GDP are the positive influencing factors for green innovation efficiency in the Yangtze River Delta, while FDI and the proportion of expenditure on science, technology and education in local budget are the negative influencing factors [39]. Miao et al. pointed out that in the green technology R&D stage, the total number of R&D personnel and government support have a positive effect on provincial green innovation efficiency, and the R&D funding intensity and environmental protection investment have a negative effect, while in the green technology transfer stage, the number of patent applications and the degree of openness have a positive effect on provincial green innovation efficiency, and new product development input and energy input have a negative effect [41] (Table 1). In 2009, Oltra et al. proposed a triple analysis framework based on technical system, market demand and environmental policy to study the driving force source of green innovation [51], which has gained some academic recognition, and then some scholars have made further empirical studies [52–54] and extensions [55,56] based on this framework.

To sum up, the existing studies have explored the spatio-temporal characteristics and driving mechanism of regional green innovation to some extent, but there are still deficiencies. First of all, the measurement indexes are extensive but not specialized, which need to be further deepened. A large percentage of papers currently study green innovation from the perspective of efficiency, but in reality the two are not exactly equivalent. Besides, the established green innovation measurement index system is still dominated by the traditional regional innovation indexes, and the characteristics of green innovation are not fully displayed. Although green technology patent can better reflect the strength of regional green innovation, and it is widely used in related studies, the existing studies only focus on the “total” of this index, with its “increment” remaining to be explored. Secondly, the influencing factors are widely used, but there is no systematic review of them. As many as 32 influencing factors have been covered in the aforementioned studies, most of which have some influence on regional green innovation, but there is not much literature that systematically analyzes these indexes. In addition, conclusions on some indicators are different or even completely opposite in different studies. Kesidou et al., for example, pointed out that environmental regulation has promoted ecological innovation in
China, but Li and Yang et al. argued that environmental regulation has both promoting and inhibiting effects on green innovation in China \[17,21,45\]; Wang et al. stated that government spending on science and technology has no effect on green innovation, but Zeng et al. believed that government spending on science, technology and education has effectively stimulated green innovation \[34,39\]. These contradictory findings may be due to the differences in research methods and representation parameters used in different studies, making it objectively necessary to systematically explore the different influencing factors under a complete framework. Based on these two deficiencies, this paper attempts to further deepen the existing research.

Table 1. Driving factors, data formation and impact direction of green innovation.

| Factor(s)          | Data Formation and Impact Direction                                                                 |
|--------------------|--------------------------------------------------------------------------------------------------------|
| Environmental regulation | Pollution reduction target (+) \[17\], ratio of environmental treatment investment to GDP (−) \[14,21\], weighted value of utilization rate of industrial solid waste, treatment rate of domestic sewage and harmless treatment rate of domestic waste (+) \[19\], ratio of industrial pollution control investment to added industrial value (−) \[41\], weighted value of removal rate of industrial sulfur dioxide, treatment rate of domestic sewage and utilization rate of industrial solid waste (−) \[30\], weighted value of industrial wastewater, exhaust gas and solid waste emission (+/−) \[45\], annual average of PM$_{2.5}$ (+) \[19\] |
| Innovation input   | R&D internal expenditure (+) \[19\], R&D internal expenditure (−) \[41\], R&D personnel equivalent (+) \[41\], new product investment (−) \[41\], ratio of R&D expenditure to environmental treatment investment (+) \[14\], ratio of green patent application to R&D expenditure (−) \[14\] |
| Government support | Ratio of science and technology expenditure to fiscal expenditure (none) \[34\], ratio of expenditure on science, technology and education to fiscal budget (−) \[39\], ratio of scientific and technological expenditure to R&D internal expenditure (+) \[41\] |
| Economic environment | GDP (+) \[19\], per capita GDP (+) \[14,30,34,39\], total retail sale of consumer goods (−) \[30\], ratio of tertiary industry to GDP (+) \[19,30,34\], ratio of tertiary industry workers to all workers (−) \[30\] |
| Education level    | Education expenditure (+) \[30\], number of college students (+) \[34\], expenditure on science, technology and education (−) \[39\] |
| Openness degree    | FDI (−) \[30,39\], FDI (+/−) \[18,46\], ratio of business income of industrial enterprises invested by foreign, Hong Kong, Macao, and Taiwan (+) \[41\] |
| Other factors      | Ratio of postal and telecommunication business value to GDP (none), \[34\], population size (+) \[14\], income tax and environment tax (+/−) \[47\], regional planning policy (+/−) \[49\], ratio of transferred area of industrial and mining storage land to all transferred area (+/−) \[50\], industrial water consumption and coal consumption (−) \[41\] |

Note: + stands for positive effect, − stands for negative effect, +/− stands for two-way effect.

1.3. Purpose and Questions

This paper characterizes China’s green innovation through green technology patent (GTP), and uses GIS spatial analysis technique, ESDA, Geodetector and other spatial econometric tools to reveal the temporal and spatial evolution patterns and driving mechanism of green innovation on Chinese 31 provinces, and attempts to propose differentiated policy suggestions for green innovation development in China, hoping to put forward a reference for decision-making on green innovation in China and other countries sharing similar conditions.
Accordingly, this paper focuses on the following questions: (1) What the spatio-temporal patterns and spatial effects of green innovation power (GIP) and green innovation growth ability (GIGA) in Chinese provinces can be found by mining features of GTP amount and GTP growth amount? (2) What are the main drivers affecting GIP and GIGA in Chinese provinces in the framework of multi-index system? What are the interaction drivers? What is the performance of their driving mechanism? (3) How to put forward differentiated green innovation policy suggestions for effective delivery of innovation resources based on the two findings above?

2. Research Design

2.1. Study Area: China

The study area of this paper is 31 provinces, autonomous regions and municipalities in mainland China, while Hong Kong, Macau and Taiwan are not included due to incomplete data (Figure 1). The continuous growth of GTP amount and GTP growth amount in China indicates the continuous rise of GIP and GIGA in China, and its development has gone through three stages: slow development from 2000 to 2007, with GTP amount increasing from 3762 to 15,007, and the average annual GTP growth amount of 1521; steady improvement from 2008 to 2017, with GTP amount increasing from 19,876 to 159,214, and the average annual GTP growth amount of 14,421; and rapid jump from 2018 to 2019, with GTP amount increasing from 229,071 to 230,119, and the average annual GTP growth amount of 35,453 (Figure 2).

Figure 1. Study area.
2.2. Research Methods

2.2.1. Coefficient of Variation

Coefficient of Variation (CV), also known as standard deviation rate, is the ratio of standard deviation and average value of a column of data, used to show the relative dispersion degree of sample data [57]. It is used in this paper to measure the overall heterogeneity degree of green innovation in Chinese provinces. It is calculated by the following equation:

$$CV = \frac{1}{\bar{y}} \sqrt{\frac{\sum_{i=1}^{n} (y_i - \bar{y})^2}{n}}$$

where, CV represents the coefficient of variation, $y_i$ represents the green technology patent (GTP) amount in different provinces, with $i = 1, 2, 3, \ldots, n$, and $n$ standing for the number of provinces, which is 31 here. $\bar{y}$ represents the average number of GTP by province. A smaller value of CV indicates a smaller degree of heterogeneity of China’s green innovation on the whole, and vice versa. According to Zhang and Zhao et al. [58,59] and, the dispersion of the sample data can be graded into three levels based on the coefficient of variation values: weak dispersion at 0.00–0.15, showing a low degree of provincial green innovation differences; medium dispersion at 0.16–0.35, showing a medium degree of provincial green innovation differences; strong dispersion at greater than 0.36, showing a high degree of provincial green innovation differences.

2.2.2. Exploratory Spatial Data Analysis

Exploratory spatial data analysis (ESDA) is based on the spatial weight matrix to explore the distribution pattern of spatial data to reflect the spatial autocorrelation of geographical phenomena, which can reveal spatial dependency between different geographical areas [58]. In this paper, global moran’s I and local moran’s I are used to analyze the global and local spatial autocorrelation of green innovation in China.

(1) Global moran’s I can reflect the spatial autocorrelation of green innovation as a whole. It is calculated by the following equation:

$$I = \frac{n}{s_0} \times \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$$

where, $s_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}$

Figure 2. Annual change of GTP amount and GTP growth amount in China from 2000 to 2019. The GTP growth amount is calculated based on the previous year’s value.

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where, \( I \) represents global moran’s I, \( n \) represents the total number of provincial samples, which is 31 here. \( x_i \) and \( x_j \) are the number of GTP of provinces \( i \) and \( j \) respectively, \( \bar{x} \) is the average of the provincial number of GTP, \( s_0 \) is the sum of all \( w_{ij} \), and \( w_{ij} \) is a spatial weight matrix, with a spatial adjacent value of 1, a non-adjacent value of 0, and \( i,j = 1, 2, 3, \ldots, n \). The value of global moran’s I is \([-1, 1]\), with a positive value indicating positive spatial autocorrelation, and a negative value indicating a negative spatial autocorrelation. A larger absolute value indicates stronger autocorrelation, while zero indicates spatial decorrelation and random distribution.

(2) Local moran’s I can reflect the local spatial autocorrelation of green innovation in provinces of China, and the local indicators of spatial association (LISA) map is a spatial visualization of local moran’s I. It is calculated by the following equation:

\[
l_i = \frac{(x_i - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sum_{j=1}^{n} w_{ij}(x_j - \bar{x})
\]  

(3) where, \( l_i \) represents local moran’s I of the province \( i \), and the rest of variables have the same meaning as those in Equation (2). Local Moran’s I have the value of \([-1, 1]\), with a positive value indicating a high-high (H-H) or low-low (L-L) cluster of the number of GTP, that is, green innovation ability, around the province, and a negative value indicating a high-low (H-L) or low-high (L-H) cluster around the province. In the LISA cluster map, cluster features are subject to a significance test (typically 0.05 or 0.1) before they are shown.

2.2.3. Geodetector

Geodetector is a set of statistical methods for detecting spatial heterogeneity and revealing the driving forces behind it [60,61], and has been widely used in the study of influencing factors of natural and socio-economic phenomena [62]. Geodetector consists of factor detection, interaction detection, risk detection and ecological detection. In this paper, factor detection and interaction detection are used to analyze the driving factors and their interaction of green innovation in China.

(1) Factor detection is used to identify the extent to which factor \( X \) explains the spatial heterogeneity of attribute \( Y \), i.e., the strength of the driving force. It is calculated by the following equation:

\[
q = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^{L} N_h \sigma_h^2
\]  

(4) where, \( q \) is a measure of the driving force of a driver on green innovation, \( N \) represents the total number of provincial samples, here 31, \( h = 1, 2, 3, \ldots, L \), and \( L \) represents the number of partitions or layers, \( \sigma^2 \) represents the total discrete variance of the provincial number of GTP in China, and \( \sigma^2_h \) represents the number of GTP in partition or layer \( h \). The value of \( q \) is in a range of \([0, 1]\), i.e., it can explain \((100 \times q\%)\) of the dependent variable, and a larger value indicates that the driver \( X \) has a stronger driving force on the provincial green innovation \( Y \) in China, and vice versa. For the significance test, 0.05 is acceptable under the general condition and 0.1 under the relaxed condition [63].

(2) Interaction detection is used to identify the interaction between different drivers, i.e., whether \( X_i \) and \( X_j \) enhance or weaken the explanatory power of dependent variable \( Y \) when they act together [60,61]. The evaluation is done by first calculating the \( q \)-values of \( X_i \) and \( X_j \) for \( Y: q(X_i) \) and \( q(X_j) \), and then calculating the \( q \)-values for \( Y \) when the two are superimposed: \( q(X_i \cap X_j) \). If \( q(X_i \cap X_j) < \min(q(X_i), q(X_j)) \), \( X_i \) and \( X_j \) will be nonlinearily weakened after the interaction; if \( \min(q(X_i), q(X_j)) < q(X_i \cap X_j) < \max(q(X_i), q(X_j)) \), \( X_i \) and \( X_j \) will be unilinearly weakened after interaction; if \( q(X_i \cap X_j) > \max(q(X_i), q(X_j)) \), \( X_i \) and \( X_j \) will be bilinearly strengthened after the interaction; if \( q(X_i \cap X_j) > q(X_i) + q(X_j) \), \( X_i \) and \( X_j \) will be nonlinearily strengthened after the interaction; if \( q(X_i \cap X_j) = q(X_i) + q(X_j) \), \( X_i \) and \( X_j \) will be independent of each other (Table 2).
2.3. Index Selection and Data Source

This paper evaluates green innovation in China from two areas of total and increment, to reflect the development characteristics of regional green innovation more comprehensively. The annual GTP amount reflects the development of green innovation in each province, which is defined as green innovation power (GIP), and the annual GTP growth amount reflects the growth strength of green innovation in each province, which is defined as green innovation growth ability (GIGA). This paper chooses to use GTP growth amount instead of GTP growth rate to reflect the growth features of green innovation in the provinces for two reasons. First, the change amount can reflect the real growth of green innovation during the study period, and second, the change rate is affected by the denominator, which will lead to a large difference between the value of the change rate and the real growth of green innovation when it is close to zero. In addition, this paper, based on the triple analysis framework proposed by Oltra et al. [51], constructs an index system of influencing factors from three perspectives: technology support, market demand and environmental regulation (Table 3).

From the perspective of technology support, technology upgrading is the core of any innovation, while the input of innovation elements is the key to promoting regional innovation [64], and external technology acquisition is an important way to promote regional innovation [65]. Therefore, this paper presents the degree of technical support for green innovation in provinces of China in terms of innovation input and foreign connection. In terms of innovation input, the commonly used R&D intramural expenditure and R&D personnel equivalent are used as representation parameters, and in view of the fact that the high-tech industry has more significant “green” characteristics [66], R&D intramural expenditure in high-tech industry and R&D personnel equivalent in high-tech industry are also included as representation parameters. In terms of foreign connection, international trade in goods (which is expressed by total trade value in import and export goods) and foreign direct investment (FDI, which is expressed by annual inflow) directly reflect the correlation degree between provinces and foreign countries, and foreign fund of R&D intramural expenditure and contract value of imported technology are also used to show the dependence of green innovation on foreign innovation elements input.

From the perspective of market demand, Oltra et al. argued that “demand condition” and “consumer preference” are important manifestations of market demand for green innovation [51], but it is hard to calculate these two indicators directly, and the existing studies mainly reflect the “demand condition” from the side through per capita GDP [52], per capita income of urban residents [67], and added value of industry and services [53], with less consideration about the influence of “consumer preference” on green innovation. Therefore, this paper decomposes the market demand for green innovation based on the theoretical framework of Oltra et al., and reflects the “demand condition” through economic environment and the “consumer preference” through market environment. In

### Table 2. Interaction relationship between explanatory variables (X_i and X_j).

| Graphical Representation | Description | Interaction |
|--------------------------|-------------|-------------|
| ▼                       | q(X_i ∩ X_j) < min(q(X_i), q(X_j)) | Weaken, nonlinear |
| ▼                       | min(q(X_i), q(X_j)) < q(X_i ∩ X_j) < max(q(X_i)), q(X_j)) | Weaken, uni- |
| ▼                       | q(X_i ∩ X_j) > max(q(X_i), q(X_j)) | Enhance, bi- |
| ▼                       | q(X_i ∩ X_j) > q(X_i) + q(X_j) | Enhance, nonlinear |
| ▼                       | q(X_i ∩ X_j) = q(X_i) + q(X_j) | Independent |

Legend: ⬇ min(q(X_i), q(X_j)) ⬆ max(q(X_i), q(X_j)) ⬇ q(X_i) + q(X_j) ⬆ q(X_i ∩ X_j)
terms of economic environment, this paper uses GDP to show the economic development of each province, and uses added value of secondary industry and added value of tertiary industry to show the impact of industrial and service industry development on green innovation. As green innovation relies more on the support of financial capital \([68,69]\), the added value of financial industry is also included as a representation parameter. In terms of market environment, the new product revenue reflects the market demand for innovative products \([70]\), while the contract value of technology market reflects the activity level of technology trading market in the provinces \([71]\). Larger values of the two indicate that there are stronger consumption preferences and higher market acceptance for innovative products and technologies, and that they are more conducive to boosting green innovation \([51]\). Therefore, this paper takes new product revenue of industrial enterprise (above designated size), new product revenue of high-tech industry and contract value of technical market as indicators to represent market environment.

| Variable          | Index                                                                 | Code | Type          |
|-------------------|----------------------------------------------------------------------|------|---------------|
| Dependent variable \(Y_i\) | Green technology patent (GTP) amount/PC                               | \(Y_1\) | Total         |
|                    | Green technology patent (GTP) growth amount/PC                       | \(Y_2\) | Increment     |
| Independent variable \(X_i\) | R&D intramural expenditure/10,000 CNY                               | \(X_1\) | Innovation input |
|                    | R&D personnel equivalent/man-year                                   | \(X_2\) |
|                    | R&D intramural expenditure in high-tech industry/10,000 CNY         | \(X_3\) |
|                    | R&D personnel equivalent in high-tech industry/man-year              | \(X_4\) |
|                    | International trade value in goods/10,000 USD                       | \(X_5\) |
|                    | Foreign direct investment (FDI)/10,000 USD                          | \(X_6\) |
|                    | Foreign fund of R&D intramural expenditure/10,000 CNY               | \(X_7\) |
|                    | Contract value of imported technology/10,000 USD                    | \(X_8\) |
|                    | Gross domestic product (GDP)/100 million CNY                       | \(X_9\) | Economic environment |
|                    | Added value of secondary industry/100 million CNY                  | \(X_{10}\) |
|                    | Added value of tertiary industry/100 million CNY                    | \(X_{11}\) |
|                    | Added value of financial industry/100 million CNY                  | \(X_{12}\) |
|                    | New product revenue of industrial enterprise (above designated size)/10,000 CNY | \(X_{13}\) | Market environment |
|                    | New product revenue of high-tech industry/10,000 CNY                | \(X_{14}\) |
|                    | Contract value of technical market/10,000 CNY                      | \(X_{15}\) |
|                    | Investment in urban environmental infrastructure facilities/10,000 CNY | \(X_{16}\) | Environmental regulation |
|                    | Investment in treatment of industrial pollution sources/10,000 CNY   | \(X_{17}\) |
|                    | Green area in urban completed area/hm²                              | \(X_{18}\) |

Note: Geodetector establishes a regression equation based on the discrete values of dependent variables without the need to uniform variable units.

From the perspective of environmental regulation, the pressure from environmental regulation is a major incentive for companies to carry out green innovation \([48,69]\), and the excessive intensity of environmental regulation may also inhibit green innovation \([70]\). Existing studies have suggested that environmental improvements are conducive to attracting talents to stay, and in turn form regional R&D advantages to promote green innovation \([71,72]\). Due to the difficulty in measuring the intensity of environmental control directly at the provincial scale, investment in urban environmental infrastructure facilities, investment in treatment of industrial pollution sources and green area in urban completed area are used in this paper for side representation according to the related researches \([72,73]\). The first two indexes reflect the investment intensity of the provincial government in environmental management, and a higher level of investment intensity indicates that the government has a more resolute attitude towards urban environmental
control and pollution control, with greater control intensity correspondingly. The latter indicator reflects the urban green space of each province, and a larger green space indicates that the province has a better quality of urban environment and is more conducive to attracting innovative talents.

The dependent variables in this paper are from the patent database of National Intellectual Property Administration of China, and green technology patents are screened by IPC Green Inventory [74]. According to the related researches [13,17,18,75], the granted green patent data are used to show the characteristics of green innovation in China. The independent variables in this paper come from China Statistical Yearbook, China Statistical Yearbook on Science and Technology and China Statistical Yearbook on environment, with small amounts of missing data completed by the method of trend extrapolation and the data of adjacent years. Both the dependent and independent variables are available through public sources, and the websites involved are accessible in the section of data availability statement below.

2.4. Research Steps

This paper follows the research idea of “question formation-question analysis-question solving”, and the research route consists of 5 steps and 9 points (Figure 3). The first step is about research question, where the research objectives and problems of this paper are put forward and confirmed based on the background analysis and literature review.

The second step is about study area and data processing, where the 31 provinces of China are identified as the study area, and the dependent and independent variables are collected from the Chinese patent database and statistical yearbooks. The missing data are completed by trend extrapolation method, and the independent variables are classified by the quantile method into 3–10 categories to find the best category.

The third step is about research methods, where the CV, spatial cluster, global Moran’s I and local Moran’s I of green innovation ability in the provinces are calculated by means of Excel 2016, Arcgis 10.2 and GeoDa 1.12. The CV is used to calculate the differentiation of green innovation, spatial cluster is used to reflect the spatial cluster of green innovation, while global Moran’s I and local Moran’s I are used to show the spatial autocorrelation of green innovation in each province. The driving factors of green innovation are calculated by Geodetector mainly based on its factor detection and interaction detection methods, where factor detection is used to calculate the driving effect of a single factor, and interaction detection is used to calculate the interaction driving effect between two factors.

The fourth step is about result analysis, where the spatio-temporal characteristics of green innovation are reflected by spatial differentiation analysis, spatial cluster analysis and spatial autocorrelation analysis. The driving factors are screened by significance test and sorted by q-value to identify those of strong, medium and weak levels, and the super interaction factors are searched. The driving mechanism of green innovation in China is determined by identifying the core, important and auxiliary driving factors, and the interaction types of different factors are distinguished.

The fifth step is about conclusion application, where the 31 provinces in China are classified into policy areas of stars, questions, cows and dogs types based on the BCG model, and policy recommendations are put forward on optimizing the development of green innovation.

This paper focuses on 2009–2019 as the period time for spatio-temporal analysis and driving mechanism research, based on two considerations: (1) it has experienced China’s 12th and 13th Five-Year Plans, with stable growth of green technology patents and rapid development of green innovation, quite typical as a sample; (2) statistical methods have changed for some key variables before 2009, and some yearbook data after 2019 are not updated. The research period set in this paper can ensure the consistency of all data calibers and data timeliness.
3. Results

3.1. Dynamic Trend Analysis

3.1.1. Spatial Heterogeneity Analysis

Green innovation in China has a large degree of heterogeneity across provinces, with a serious polarization in GIP and GIGA. The coefficient of variation of GTP amount ranged from 1.14 to 1.20, with an average value of 1.16, and that of GTP growth amount ranged from 1.30 to 20.84, with an average value of 3.69. Both of them were at a high level of heterogeneity (Table 4) during the research period, showing serious heterogeneity of GIP and GIGA in different provinces of China.
The GTP amount of 31 provinces in China is divided into higher, high, low and lower levels (Figure 4) based on natural breaks. It can be seen that the GIP shows a decreasing gradient from eastern to central and western China, and that the regions with strong GIP are mainly located in a few coastal and riverine (especially the Yangtze River) provinces and cities, with a trend of gradually shifting from coastal and riverine distribution to coastal distribution. Different types of regions vary greatly, with higher and high regions continuing to contract, lower regions continuing to expand, and lower regions being stable in number but highly variable in location. Specifically, in 2009, higher regions included Beijing, Shanghai, Guangdong, Shandong, Jiangsu and Zhejiang, high regions included 7 provinces and cities such as Liaoning, Tianjin, Sichuan, Henan, Hubei and Hunan, low regions included 8 provinces such as Heilongjiang, Jilin, Hebei, Shanxi, Shaanxi and Anhui, and lower regions included 10 provinces such as Jiangxi, Guizhou, Yunnan, Hainan, Inner Mongolia and Gansu. In 2014, the higher regions decreased to Beijing, Jiangsu, Zhejiang and Guangdong, while the high regions decreased to Shandong and Shanghai. The low regions experienced a drastic change, with the addition of 7 provinces and cities including Liaoning, Tianjin, Sichuan, Henan, Hubei and Fujian, but the reduction of Heilongjiang, Jilin, Shanxi and Yunnan, and the lower regions expanded to 16 provinces. In 2019, the higher regions further decreased to Jiangsu and Guangdong, the high regions evolved to Beijing, Shandong and Zhejiang, the low regions shrank to 9 provinces and cities, including Tianjin, Shanghai, Hebei, Henan, Sichuan and Fujian, while the lower regions expanded to 17 provinces. At the same time, the cumulative percentage of GTP amount Top 10 in provinces remains between 73% and 75% all the year round, and most of them are coastal provinces and cities, except Hubei, Henan, Sichuan and Anhui that are distributed along the Yangtze River (Table 5), indicating that the regions with a high GIP value are concentrated in the eastern coastal areas and a few provinces and cities along the river.

### Table 4. CV trend of GTP amount and GTP growth amount from 2009 to 2019.

| Type             | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|------------------|------|------|------|------|------|------|------|------|------|------|------|
| GTP amount       | 1.14 | 1.13 | 1.15 | 1.16 | 1.17 | 1.17 | 1.15 | 1.12 | 1.16 | 1.18 | 1.20 |
| GTP growth amount| 1.30 | 1.15 | 1.25 | 1.28 | 1.27 | 1.27 | 1.51 | 1.17 | 1.04 | 2.51 | 1.30 |

### 3.1.2. Spatial Cluster Analysis

Figure 4. Spatial cluster of GTP amount in 2009, 2014 and 2019.
Table 5. GTP amount and cumulative percentage of top 10 provinces in 2009, 2014 and 2019.

| Name   | 2009  | Cumulative Percentage | Name   | 2014  | Cumulative Percentage | Name   | 2019  | Cumulative Percentage |
|--------|-------|-----------------------|--------|-------|-----------------------|--------|-------|-----------------------|
| Guangdong | 3525  | 13.32%                | Jiangsu | 12,780 | 13.76%                | Jiangsu | 37,690 | 16.38%                |
| Beijing  | 3072  | 24.93%                | Beijing | 11,730 | 26.38%                | Guangdong | 33,630 | 30.99%                |
| Jiangsu  | 2816  | 35.57%                | Guangdong | 11,278 | 38.52%                | Zhejiang | 20,100 | 39.73%                |
| Zhejiang | 2609  | 45.43%                | Zhejiang | 9351  | 48.58%                | Shandong | 18,396 | 47.72%                |
| Shanghai | 2230  | 53.86%                | Shandong | 6197  | 55.25%                | Beijing  | 14,942 | 54.21%                |
| Shandong | 1917  | 61.10%                | Shanghai | 4764  | 60.38%                | Shanghai | 10,353 | 58.71%                |
| Liaoning | 1087  | 65.21%                | Anhui   | 3419  | 64.06%                | Fujian   | 8790  | 62.53%                |
| Hubei    | 901   | 68.61%                | Sichuan | 3271  | 67.58%                | Henan    | 8361  | 66.17%                |
| Henan    | 889   | 71.97%                | Henan   | 2825  | 70.62%                | Hubei    | 7982  | 69.64%                |
| Sichuan  | 862   | 75.23%                | Hubei   | 2797  | 73.63%                | Anhui    | 7822  | 73.03%                |

The GTP growth amount of 31 provinces in China is classified into four categories by natural breaks. To facilitate comparison, the research period is divided into two equal intervals: 2009–2014 and 2014–2019, with the GTP growth amount of each interval expressed as an annual average (Figure 5). It can be seen that the GIGA also shows a decreasing gradient from east to middle and west, and that the regions with stronger GIGA also show a shift from coastal and riverine (especially the Yangtze River) distribution to coastal distribution. Dramatic changes were observed in the different types of regions, where higher and high regions decreased, lower regions increased, and lower regions were stable in the number, but their location changed. Specifically, in 2009–2014, higher regions included Beijing, Jiangsu, Zhejiang and Guangdong, high regions included 9 provinces and cities such as Tianjin, Shandong, Shandong and Fujian, low regions included 8 provinces and cities such as Heilongjiang, Liaoning, Hebei, Shanxi, Jiangxi and Chongqing, and lower regions included 9 provinces such as Jilin, Inner Mongolia, Gansu, Ningxia, Xinjiang and Hainan. In 2014–2019, the higher regions shrank to Jiangsu and Guangdong, the higher regions shrank to Beijing, Shandong and Zhejiang, the low regions changed drastically, with addition of 8 provinces and cities such as Tianjin, Shanghai, Sichuan, Hunan, Hubei and Anhui, and reduction of 6 provinces and cities such as Heilongjiang, Liaoning, Shanxi, Yunnan, Chongqing and Guangxi, while the lower regions expanded to 16 provinces and cities.

GTP growth amount

2009-2014

2014-2019

Figure 5. Spatial cluster of GTP growth amount from 2009 to 2019.

3.2. Spatial Autocorrelation Analysis

3.2.1. Global Autocorrelation Analysis

Both GIP and GIGA in Chinese provinces showed some degree of spatial aggregation, but there was a tendency to weaken. The global moran’s I for all variables in Table 6 passed the significance test of 0.1 except that for GTP growth amount (2014–2019). Moran’s I of
GTP amount decreased from 0.139 to 0.117, and that of GTP growth amount decreased from 0.164 to 0.071, suggesting that GIP and GIGA in all provinces of China showed a certain degree of aggregation during the research period, but the aggregation tendency was weakening.

Table 6. Global moran’s I of GTP amount and GTP growth amount.

| Type              | Period  | Moran’s I | p-Value | Z-Score |
|-------------------|---------|-----------|---------|---------|
| GTP amount        | 2009    | 0.139 *   | 0.087   | 1.461   |
|                   | 2014    | 0.161 *   | 0.057   | 1.715   |
|                   | 2019    | 0.117 *   | 0.090   | 1.386   |
| GTP growth amount | 2009–2014 | 0.164 * | 0.053   | 1.765   |
|                   | 2014–2019 | 0.071   | 0.150   | 1.004   |

Note: * stands for p < 0.1.

3.2.2. Local Autocorrelation Analysis

LISA maps of GTP amount were drawn by GeoDa 1.12, and all of them passed the significance test of 0.1. The 31 provinces were classified into four types of H-H, L-L, L-H, and H-L (Figure 6). It can be seen that GIP showed prominent spillover and lock-in effects, with Shandong and the Yangtze River Delta being high value aggregation regions which continued to expand, while the northern, northwestern and northeastern China were low value aggregation regions, in a relatively solidified pattern. Sichuan was a “star” region with a higher GIP than its neighboring provinces and cities, while Jiangxi and Hainan were “collapse” regions with a lower GIP than other provinces around. Specifically, in 2009, H-H regions included Jiangsu and Shanghai, L-L regions included Inner Mongolia, Ningxia, Gansu, Xinjiang, Qinghai and Yunnan, L-H regions included Anhui, Jiangxi, Fujian and Hainan, while H-L regions only included Sichuan. In 2014, the H-H regions expanded with an addition of Shandong, Anhui and Zhejiang, the L-L regions changed with an addition of Heilongjiang and with a reduction of Ningxia and Yunnan, the L-H regions shrank with a reduction of Anhui, while the H-L regions remained stable. In 2019, Fujian was further added to the H-H regions, and Ningxia turned into a part of L-L regions. Only Jiangxi and Hainan were left in the L-H regions, while Sichuan still remained a H-L region.

Figure 6. LISA maps of GTP amount in 2009, 2014 and 2019.

LISA maps of GTP growth amount (Figure 7) were made using GeoDa 1.12, with the settings the same as those shown in Figures 5 and 6. The aggregation characteristics of GIGA were found to be solidified, with Shandong and the Yangtze River Delta region being high value aggregation regions of GIGA, the north, northeast and northwest regions being low value aggregation regions, Sichuan being a “star” region, and Jiangxi and Hainan being “collapse” regions. Specifically, in 2009–2014, H-H regions included Shandong, Jiangsu, Anhui, Zhejiang and Shanghai, L-L regions included Heilongjiang, Liaoning, Inner Mongolia, Gansu, Qinghai and Xinjiang, L-H regions included Tianjin, Jiangxi, Fujian
and Hainan, and H-L regions included only Sichuan. In 2014–2019, the H-H regions still included the 5 provinces and cities, but they changed to Shandong, Anhui, Zhejiang, Fujian and Shanghai, the L-L regions had an addition of Ningxia and Jilin, with a reduction of Liaoning, the L-H regions decreased to Jiangxi and Hainan, while the H-L regions remained unchanged.

According to the factor detection results, there were significant differences in the acting forces of different factors, with simultaneous presence of stability factors and fluctuation factors. In Table 7, $X_{16}$ and $X_{17}$ of $Y_2$ (2009–2014), and $X_5$, $X_8$ and $X_{17}$ of $Y_2$ (2014–2019) failed the significance test, while other factors all passed the significance test of 0.1. For $Y_1$ (2009), the driver strengths were ranked in the order of $X_1 > X_2 > X_{12} > X_3 > X_6 > X_{11} > X_4 > X_{14} > X_5 > X_{13} > X_7 > X_{18} > X_{15} > X_8 > X_9 > X_{16} > X_{10} > X_{17}$; for $Y_1$ (2019), the driver strengths were ranked in the order of $X_{11} > X_2 > X_3 > X_{12} > X_3 > X_{14} > X_6 > X_{18} > X_8 > X_9 > X_{13} > X_{10} > X_5 > X_{15} > X_{16} > X_7 > X_{17}$. According to strong, medium and weak levels of the factor forces by equal interval, among the relatively stable factors, R&D intramural expenditure, R&D personnel equivalent, R&D intramural expenditure in high-tech industry, added value of secondary industry and added value of financial industry maintained a strong force all the time; R&D personnel equivalent in high-tech industry, new product revenue of industrial enterprise and green area in urban completed area maintained a medium force; added value of secondary industry, contract value of technical market, investment in urban environmental infrastructure facilities and investment in treatment of industrial pollution sources maintained a weak force. Among the factors with large fluctuations, international trade in goods and foreign fund of R&D intramural expenditure changed from medium to weak, FDI changed from strong to medium, contract value of imported technology and GDP changed from weak to medium, and new product revenue of high-tech industry changed from medium to strong. For $Y_2$ (2009–2014), the driver strengths were ranked in the order of $X_1 > X_{12} > X_3 > X_5 > X_4 > X_{11} > X_6 > X_{18} > X_{15} > X_{13} > X_2 > X_9 > X_{14} > X_{10} > X_8 > X_7$; for $Y_2$ (2014–2019), the driver strengths were ranked in the order of $X_{12} > X_{11} > X_{18} > X_9 > X_1 > X_{15} > X_6 > X_3 > X_2 > X_{10} > X_7 > X_{14} > X_{13} > X_4 > X_{16}$. Among the relatively stable factors, R&D intramural expenditure, added value of tertiary industry and added value of financial industry maintained a strong force all the time; R&D personnel equivalent, FDI and contract value of technical market maintained a medium force; foreign fund of R&D intramural expenditure and new product revenue of high-tech industry maintained a weak force. Among the factors with large fluctuations, R&D intramural expenditure in high-tech industry and green area in urban completed area changed from strong to medium; R&D personnel equivalent in high-tech industry and GDP changed from strong to weak; added

Figure 7. LISA maps of GTP growth amount from 2009 to 2019.

3.3. Driving Factor Analysis
3.3.1. Factor Detection
value of secondary industry and new product revenue of industrial enterprise changed from medium to weak.

Table 7. Result of factor detection.

| $X_i$ | $Y_1$ (2009) | $Y_1$ (2019) | $Y_2$ (2009–2014) | $Y_2$ (2014–2019) |
|-------|--------------|--------------|-------------------|-------------------|
|       | $q$-Value    | $p$-Value    | $q$-Value         | $p$-Value         |
| $X_1$ | 0.7750 ***   | 0.0000       | 0.6203 ***        | 0.0002            |
| $X_2$ | 0.7546 ***   | 0.0000       | 0.6244 ***        | 0.0002            |
| $X_3$ | 0.7341 ***   | 0.0000       | 0.6071 ***        | 0.0003            |
| $X_4$ | 0.7230 ***   | 0.0000       | 0.5012 ***        | 0.0027            |
| $X_5$ | 0.7004 ***   | 0.0000       | 0.4694 ***        | 0.0048            |
| $X_6$ | 0.7311 ***   | 0.0000       | 0.5656 ***        | 0.0007            |
| $X_7$ | 0.6825 ***   | 0.0000       | 0.4208 **         | 0.0106            |
| $X_8$ | 0.5478 ***   | 0.0010       | 0.5533 ***        | 0.0009            |
| $X_9$ | 0.5425 ***   | 0.0012       | 0.5147 ***        | 0.0021            |
| $X_{10}$ | 0.3973 **   | 0.0150       | 0.4789 ***        | 0.0040            |
| $X_{11}$ | 0.7309 ***  | 0.0000       | 0.6293 ***        | 0.0001            |
| $X_{12}$ | 0.7525 ***  | 0.0000       | 0.6185 ***        | 0.0002            |
| $X_{13}$ | 0.6828 ***  | 0.0000       | 0.4881 ***        | 0.0034            |
| $X_{14}$ | 0.7181 ***  | 0.0000       | 0.5993 ***        | 0.0003            |
| $X_{15}$ | 0.5785 ***  | 0.0005       | 0.4535 ***        | 0.0062            |
| $X_{16}$ | 0.5022 ***  | 0.0026       | 0.4267 ***        | 0.0096            |
| $X_{17}$ | 0.2898 *    | 0.0617       | 0.3778 **         | 0.0197            |
| $X_{18}$ | 0.6066 ***  | 0.0003       | 0.5654 ***        | 0.0007            |

Note: * stands for $p < 0.1$, ** stands for $p < 0.05$, *** stands for $p < 0.01$.

According to the driving force results, the driving force variables of different types varied greatly in different stages. The results in Table 8 are calculated as average values of different types of driving factors. The driving force variables of $Y_1$ (2009) were ranked in the order of innovation input > foreign connection > market environment > economic environment > environmental regulation; the driving force variables of $Y_1$ (2019) were in the order of innovation input > economic environment > market environment > foreign connection > environmental regulation, with innovation input maintaining a high driving force, market environment maintaining a medium driving force, environmental regulation maintaining a low driving force, foreign connection changing from strong to weak, and economic environment changing from weak to strong. $Y_2$ (2009–2014) had the driving force variables in the order of innovation input > environmental regulation > economic environment > foreign connection > market environment; $Y_2$ (2014–2019) had the driving force variables in the order of economic environment > innovation input > foreign connection > market environment > environmental regulation, with innovation input maintaining a high driving force, market environment maintaining a low driving force, environmental regulation changing from strong to weak, foreign connection changing from weak to medium, and economic environment changing from medium to strong.

Table 8. Result of driving force variables.

| Type              | $Y_1$ (2009) | $Y_1$ (2019) | $Y_2$ (2009–2014) | $Y_2$ (2014–2019) |
|-------------------|--------------|--------------|-------------------|-------------------|
| Innovation input  | 0.747        | 0.588        | 0.486             | 0.347             |
| Foreign connection| 0.666        | 0.502        | 0.359             | 0.345             |
| Economic environment| 0.606        | 0.560        | 0.406             | 0.422             |
| Market environment| 0.660        | 0.514        | 0.348             | 0.326             |
| Environmental regulation| 0.466  | 0.457    | 0.419             | 0.319             |

Note: Only factors which passed the significance test participate in the calculation of average value.
3.3.2. Interaction Detection

Interaction detection was dominated by bilinear reinforcement and supplemented by nonlinear reinforcement, with significant differences in factor interactions and the emergence of some super-interaction factors. A total of 531 factor pairs were found in interaction detection, and all of them were bilinearly enhanced, except for \( X_9 \cap X_{17} \) and \( X_{16} \cap X_{17} \) in \( Y_1 \) (2009), \( X_7 \cap X_6, X_8 \cap X_6, X_8 \cap X_{10}, \) and \( X_{10} \cap X_{18} \) in \( Y_2 \) (2009–2014), and \( X_{14} \cap X_{16} \) in \( Y_2 \) (2014–2019), which were nonlinearly enhanced. With the interaction detection values of the four dependent variables classified into high, medium and low levels by quantile clustering, the results showed significant differences in the factor interactions (Figure 8). For \( Y_1 \) (2009), the minimum value of interaction detection was 0.64, and the maximum value was 0.95, with an average of 0.84. The top five factor pairs were \( X_{18} \cap X_{14}, X_{18} \cap X_7, X_{16} \cap X_3, X_{16} \cap X_{14} \) and \( X_{18} \cap X_{13} \). For \( Y_1 \) (2019), the minimum value of interaction detection was 0.56, and the maximum value was 0.84, with an average of 0.70. The top five factor pairs were \( X_6 \cap X_4, X_{16} \cap X_6, X_{14} \cap X_1, X_{14} \cap X_6 \) and \( X_{18} \cap X_3 \). For \( Y_2 \) (2009–2014), the minimum value of interaction detection was 0.39, and the maximum value was 0.89, with an average of 0.61. The top five factor pairs were \( X_{18} \cap X_3, X_{18} \cap X_{11}, X_{15} \cap X_2, X_{18} \cap X_{12} \) and \( X_{12} \cap X_4 \). For \( Y_2 \) (2014–2019), the minimum value of interaction detection was 0.37, and the maximum value was 0.67, with an average of 0.51. The top five factor pairs were \( X_{15} \cap X_4, X_{12} \cap X_6, X_{12} \cap X_7, X_6 \cap X_5 \) and \( X_{15} \cap X_{12} \).

Due to their frequent appearance, green area in urban completed area, investment in urban environmental infrastructure facilities, added value of financial industry, FDI, R&D personnel equivalent in high-tech industry and R&D intramural expenditure in high-tech industry can be regarded as super interaction factors.

![Figure 8](image_url)

**Figure 8.** Result of interaction detection. Only factors which passed the significance test are shown here.

3.3.3. Driving Mechanism

According to the above analysis, the core factors, important factors and auxiliary factors that have influence on GIP and GIGA in China were extracted from the driving factors, and screened in accordance with the principle as below: (1) Based on the ranking of factors of \( Y_1 \) (2019), extract those ranked Top 6 in \( Y_1 \) (2019) and Top 3 in \( Y_1 \) (2009) as core factors, with the remaining in Top 6 as important factors; extract those ranked Top 12 in \( Y_1 \) (2019) and Top 6 in \( Y_1 \) (2009) as important factors, with the remaining in Top 12 as auxiliary factors; and set the rest as auxiliary factors. (2) Based on the ranking of factors of
Y2 (2014–2019), extract those ranked Top 5 in Y2 (2014–2019) and Top 3 in Y2 (2009–2014) as core factors, with the remaining in Top 5 as important factors; extract those ranked Top 10 in Y2 (2014–2019) and Top 6 in Y2 (2009–2014) as important factors, with the remaining in Top 10 as auxiliary factors; and set all the rest as auxiliary factors (Figure 9).

### Figure 9. Driving mechanism of green innovation in China. Red fonts are the super interaction factors.

The results showed that core factors having influence on GIP in China included R&D intramural expenditure and R&D personnel equivalent; important factors included R&D intramural expenditure in high-tech industry, FDI, added value of financial industry, added value of tertiary industry and new product revenue of high-tech industry; auxiliary factors included R&D personnel equivalent in high-tech industry, international trade in goods, foreign fund of R&D intramural expenditure, contract value of imported technology, GDP, added value of secondary industry, added value of tertiary industry and green area in urban completed area; important factors included R&D personnel equivalent in high-tech industry, international trade in goods, foreign fund of R&D intramural expenditure, contract value of imported technology, GDP, added value of secondary industry, added value of tertiary industry and green area in urban completed area; and set all the rest as auxiliary factors.

| Core factors | Important factors | Auxiliary factors |
|-------------|------------------|-----------------|
| X1: R&D personnel equivalent | X2: R&D intramural expenditure in high-tech industry | X10: Green area in urban completed area |
| X2: R&D personnel equivalent in high-tech industry | X3: Foreign direct investment (FDI) | |
| X3: Foreign fund of R&D intramural expenditure | X4: Added value of financial industry | |
| X4: R&D intramural expenditure in high-tech industry | X5: Added value of tertiary industry | |
| X5: Net product revenue of tertiary industry | X6: Gross domestic product (GDP) | |
| X6: Gross domestic product (GDP) | X7: Added value of secondary industry | |
| X7: New product revenue of high-tech industry | X8: Green area in urban completed area | |
| X8: Green area in urban completed area | X9: Investment in urban environmental infrastructure facilities | |

The core factors mainly exert direct effects, and the strength of single-factor effects gradually decreases during the study period; the important factors mainly exert interactive effects, and the strength of single-factor effects also gradually decreases; the auxiliary factors exert weak direct effects, with a small number exerting strong interactive effects, and the strength of single-factor effects shows both increase and decrease trends. Core factors having influence on GIGA in China included R&D personnel equivalent and added value of financial industry; important factors included R&D intramural expenditure in high-tech industry, GDP, added value of tertiary industry and green area in urban completed area; auxiliary factors included R&D personnel equivalent, R&D personnel equivalent in high-tech industry, FDI, foreign fund of R&D intramural expenditure, added value of secondary industry and new product revenue of industrial enterprise. The three types of driving factors of GIGA have different strengths, but all of them mainly exert direct and interactive effects, with the strength of single-factor effects gradually decreasing during the study period.
effects of core factors gradually decreasing during the study period, and that of important factors and auxiliary factors showing both increase and decrease trends.

4. Discussion

4.1. Theoretical Value

The findings in this paper are good evidence of some previous study conclusions, and also some extensions to them. First of all, the findings of this paper that China’s green innovation shows decreasing gradient and spatial cluster are generally in agreement with the conclusions of Zhou, Yang and Fu et al. [14,15,22]. In addition, Corradini said that green technology patents are very unevenly distributed among European countries [76]. Kijek and Matras-Bolíbok pointed out that countries with high and medium-high eco-innovation capacity are in northern and central-western Europe, while those with medium-low and low eco-innovation capacity are in central-eastern and southern Europe [77]. Caratú and Mazzanti et al. also suggested that green technology patents are significantly more in northern Italy than in other regions [78]. It can be seen that the spatial cluster and spatial differences exhibited by green innovation are geographic phenomena common to different regions and different countries. Secondly, this paper finds that the four driving force variables of innovation input, foreign connection, economic environment and environmental regulation have positive influence on green innovation in China to some extent, which agrees with some findings of Zhou, Kesidou, Duan, Li, and Dai et al. [14,17,19,21,46]. However, Zhou and Li et al. also pointed out that environmental regulation and R&D input have an inhibitory effect in some regions of China [14,21], but it was not found in this study. Besides, Saunila et al. argued that economic and institutional pressures are the main driving forces of green innovation in Finnish horse industry companies [79]. Han et al. stated that innovation capacity and environmental regulation promote eco-innovation in SMEs in Myanmar [80]. However, Cuerva et al. argued that innovation inputs such as R&D capital and human capital have promoted traditional innovation in Spanish SMEs but not green innovation [81]. Brunnertmeier et al. also said that increased environmental regulation has not been effective in stimulating environmental innovation in the US manufacturing sector because companies fear that regulators will raise regulatory standards when new technologies are developed [82]. As can be seen, the findings of this paper are generally in agreement with those of Zhou, Kesidou, Duan, Li, Dai, Saunila and Han et al., but not fully consistent with those of Cuerva, Brunnermeier, Zhou and Li et al. The differences with Zhou and Li et al. in conclusions may be due to the different research methods and the threshold of the indicators themselves, and the differences with Cuerva and Brunnermeier et al. in conclusions may be the result of different national background and the case subjects. In addition, this paper also discusses the role of market environment on green innovation, which is a supplement to the existing index system of influencing factors. Thirdly, the existing studies pay little attention to the spatio-temporal characteristics and driving mechanism of green innovation growth ability, but this paper places much focus on them, which is helpful to re-examine regional green innovation from an incremental perspective. According to the analysis results, the spatio-temporal characteristics of GIP and GIGA showed certain degree of similarities, but their driving factor intensity and driving mechanism were quite different.

There are also some special findings in this paper that the driving forces of five driving force variables on GIP and GIGA changed in different periods, indicating that the driving mechanism of green innovation are different in different stages, and there are differences in the direction of changes in core factors, important factors and auxiliary factors of GIP and GIGA during the study period, indicating that the driving mechanisms of green innovation have become more diverse and complex, which may provide a reference for the optimization of green innovation policies in regions at different development stages. Besides, among the driving forces of innovation input, R&D input and R&D input in high-tech industry had almost the same force on green innovation, indicating that the “green” characteristics of high-tech industry itself have obvious spillover effects on green
innovation. Among the driving forces of foreign connection, FDI had the greatest force on green innovation, indicating that the advanced technology and experience introduced by foreign capital in the investment is crucial for local green innovation and is more effective than the direct introduction by technology contracts. Among the driving forces of economic environment, the added value of tertiary industry and added value of financial industry had a greater effect on green innovation than GDP and added value of secondary industry, indicating that optimization of the service and financial industries is the key to stimulating green innovation, which echoes the findings of Duan, Yuan, and Tolliver et al. [19,68,69]. Among the driving forces of market environment, the three factors of new product revenue of industrial enterprise, new product revenue of high-tech industry and contract value of technical market showed the same force in general, but their effect on GIP was greater than that on GIGA on the whole, indicating that there is a certain dependence on path in the development of new product market and technology market, and it is difficult to stimulate the rapid increase of incremental green innovation with these two factors. Among the driving forces of environmental regulation, green area in urban completed area had a larger force than investment in urban environmental infrastructure facilities and investment in treatment of industrial pollution sources, suggesting that the improvement of urban environmental quality is indeed beneficial to the development of green innovation, but the government’s attitude towards environmental regulation may not be directly related to green innovation, where there may be a more complex mechanism.

4.2. Policy Enlightenment

Products are classified into four types of stars, question, cows and dogs based on the Boston Consulting Group (BCG) matrix by “market share” and “sales growth”, so that different suggestions can be made for different types of products [55]. This paper borrows the idea of the model to classify green innovation in different provinces of China, which helps to propose more precise optimization policies according to local conditions. With the ratio of the provincial GTP amount to the highest provincial GTP amount in the current year standing for the relative share, and the GTP growth amount in the corresponding year standing for the growth amount, both standardized by min-max normalization, the average relative share and growth amount of provincial GTP in the last three years, in view of data fluctuation and policy timeliness, were calculated, and they were classified using the average of 31 provinces as the threshold (Figure 10).

The results showed that the provinces in China were mostly of stars and dogs types, and there were few cows and question provinces. Stars provinces were of “double-high” type, with high GIP and GIGA, as key regions leading China’s green innovation and development, including 10 provinces and cities such as Guangdong, Jiangsu, Anhui, Shandong, Beijing and Shanghai, primarily in central and east China. Dogs provinces were of “double-low” types with low GIP and GIGA, as backward regions that restrict the promotion of green innovation in China, including 15 provinces and cities such as Heilongjiang, Chongqing, Xinjiang, Yunnan, Ningxia and Inner Mongolia, mainly in northeast and west China. Cows provinces were of “high and low” type with high GIP but low GIGA, including Zhejiang, Fujian, Tianjin and Sichuan; while question provinces were of “low and high” type with low GIP but high GIGA, including Liaoning and Jiangxi. Despite a small number of provinces of these two types, they had great potential to develop into stars regions, with the former having a sound development foundation, while the latter having a strong growth ability.

Cows, question and dogs provinces are the key regions that should be focused on by China’s green innovation policy. Cows provinces should concentrate on the promotion of GIGA, on the optimization of innovation input, economic environment and environmental regulation, and on the role of factors such as R&D intramural expenditure, added value of financial industry, R&D intramural expenditure in high-tech industry, GDP, added value of tertiary industry and green area in urban completed area. Question provinces should concentrate on the strengthening of GIP, on the optimization of innovation input,
foreign connection, economic environment and market environment, and on the role of factors such as R&D intramural expenditure, R&D personnel equivalent, R&D intramural expenditure in high-tech industry, FDI, added value of financial industry, added value of tertiary industry and new product revenue of high-tech industry. Dogs provinces should concentrate on the improvement of both GIA and GIGA, with consideration of the above driving force variables and driving factors.

Figure 10. Policy zoning map of green innovation in China. Average value has removed the interference of maximum and minimum.

In addition, the four policy areas are concentrated in spatial distribution, for example, the provinces of stars and question account for a larger part in the eastern and central regions, while the provinces of dogs in the northwest, southwest and northeast. The government should comprehensively consider such spatial characteristics as well as sub-regional development conditions, and formulate differentiated green innovation policies at the inter-provincial scale for effective and precise deployment of green innovation resources.

5. Conclusions

In the context of global “transition to sustainable development”, green innovation has been increasingly the focus of the attention of academia and industry. Green innovation involves a wide variety of fields, and different conclusions or findings can be drawn from different disciplines such as environmental science, engineering, economics, management and geography. From the perspective of economic geography and based on GIS tools, Geodetector and other spatial measurement tools, this paper investigates the spatio-temporal characteristics and driving mechanism of green innovation 2009–2019 in China from two dimensions of GIP and GIGA, which is of great importance in promoting the optimal development of regional green innovation. The main conclusions reached are as follows:

(1) GTP amount and GTP growth amount in China continued to grow, indicating that both GIP and GIGA in China were on the rise, but there was serious polarization between
different provinces, and there were striking changes between high and low regions, with the high regions showing a shift from coastal and riverine distribution to coastal distribution. And GIP and GIGA showed a decreasing gradient from east to middle and west in different periods with obvious aggregation characteristics, and Shandong and Yangtze River Delta were the main high value aggregation regions.

(2) There were great differences in the force of the 18 drivers on green innovation. For GIP, the 5 factors such as R&D intramural expenditure and R&D personnel equivalent had a strong force, the 3 factors such as R&D personnel equivalent in high-tech industry and new product revenue of industrial enterprise had a medium force, and the 4 factors such as added value of secondary industry and contract value of technical market had a weak force, while the force of the other factors varied greatly in different stages. For GIGA, the 3 factors such as R&D intramural expenditure and added value of tertiary industry had a strong force, the 3 factors such as R&D personnel equivalent and FDI had a medium force, and the factors of foreign fund of R&D intramural expenditure and new product revenue of high-tech industry had a weak force, while the force of the other factors also varied greatly. In addition, the 7 factors such as green area in urban completed area and investment in urban environmental infrastructure facilities were super interaction factors.

(3) The 5 driving force variables showed different forces on green innovation, and for GIP, innovation input and market environment maintained large and medium driving forces, environmental regulation maintained a low driving force, and foreign connection and economic environment had a force varying widely across stages; for GIGA, innovation input maintained a large driving force, market environment maintained a low driving force, and the force of environmental regulation, foreign connection and economic environment also varied greatly.

(4) The core factors, important factors and auxiliary factors that have influence on green innovation were picked out according to the ranking of different driving factors, and for GIP, R&D intramural expenditure and R&D personnel equivalent were core factors, the 5 factors such as R&D intramural expenditure in high-tech industry and FDI were important factors, and the other 11 factors were auxiliary factors, with the important factors mainly playing an interactive role, while those of the other two types mainly playing a direct role; for GIGA, R&D intramural expansion and added value of financial industry were core factors, the 4 factors including R&D intramural expansion in high-tech industry and GDP were important factors, and the other 9 factors were auxiliary factors, all of which mainly playing both direct and interactive roles.

(5) The 31 provinces in China are classified into four types based on the BCG matrix: stars, questions, cows and dogs. Provinces of cows, question and dogs are the key areas for green innovation policy optimization, specifically, the provinces of cows should emphasize improving GIGA, with focus on the optimization of innovation input, economic environment and environmental regulation; the provinces of question should emphasize improving GIP, with focus on the optimization of innovation input, foreign connection, economic environment and market environment; the provinces of dogs should emphasize improving both GIA and GIGA, with consideration of all five driving variables.

In theory, this paper expands the research perspective of green innovation and extends the analysis of the spatio-temporal characteristics of “increment” based on the “total” of green innovation available, while systematically analyzing the multiple drivers of green innovation, which facilitates deep understanding of the spatio-temporal evolution of green innovation and its influence mechanism. In practice, the conclusions of this paper may provide a basis for the government to adjust green innovation policies, especially the conclusion of policy zoning of 31 provinces of China based on the BCG model can be directly used as a reference for the Chinese government to optimize green innovation policies. The spatial differentiation and driving mechanism of green innovation discovered in this paper are also found in other developed and developing countries, such as Italy [78], Finland [79] and Myanmar [80]. In the current context that sustainable development has become a global consensus, both developed countries such as the UK, the US, Australia,
Japan, Sweden and Belgium, and developing countries such as India, Iran, Malaysia, Vietnam, Turkey and Egypt are generally facing the pressure of transition to sustainable development. The research methods and findings of this paper can also provide a reference for decision making on optimizing development of green innovation in these countries.

However, there are still some deficiencies. For example, this paper conducts research mainly at the provincial scale in China, lacking comparisons from an international perspective as well as city- and county-level comparisons, leading to some limitation in the applicability of the study findings. The analysis of the influencing factors in this paper is conducted mainly based on the triple analyzing framework proposed by Oltra et al. and the discussion is conducted in three dimensions of technology support, market demand and environmental regulation, with little attention to other influencing factors such as government support, education background and cultural atmosphere, which needs to be further improved. Moreover, the empirical study in this paper is mainly based on statistical data, with little attention to enterprise subjects and innovation individuals. As a result, the accuracy of some research conclusions needs to be further verified. We will continue to deepen research for these three shortcomings in the following study.

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