**RESEARCH ARTICLE**

# Environmental regulation, market demand, and green innovation: spatial perspective evidence from China

Xiaoyu Shao[1] · Sha Liu[1] · Ruiping Ran[1,2] · Yunqiang Liu[1]

## Abstract

This paper used a dynamic spatial panel model to empirically analyze the effects of environmental regulation, market demand, and the associated spatial spillovers on regional green innovation in China, from which the following was found. (1) The environmental regulations had a positive "U-shaped" effect on local green innovation and a positive neighborhood spillover effect, and market demand had a significant positive effect on local green innovation and a "ripple effect." (2) The mechanism analysis found that the environmental regulations tended to inhibit regional green innovation input through a "cost compliance" effect, and market demand had a stronger incentive effect on innovation input than the environmental regulations, thus promoting the improvement of green innovation level. (3) The environmental regulation and market demand effects on green innovation had obvious spatial and temporal heterogeneity. The results of this study could help to promote regional green innovation by formulating reasonable environmental policies and stimulating the vitality of green technology market.

**Keywords** Green innovation · Environmental regulation · Market demand · Spatial spillover · Mechanism analysis · Heterogeneity analysis

## Introduction

Resource and environmental problems have become increasingly serious in the past few decades and are now threatening sustainable socio-economic development (Fan et al. 2021; Ouyang et al. 2020; Song et al. 2020). As the largest developing country in the world, China is still ongoing urbanization and industrialization transformations (Song et al. 2018; Wu et al. 2021b). Therefore, how to coordinate the relationship between economic growth and resource and environmental constraints to achieve high-quality economic development has aroused more and more thoughts. Innovation is the fundamental driving force for long-term economic growth (Aghion et al. 2015a). Green innovation adds environmental protection elements on the basis of traditional innovation, which can meet the needs of sustainable economic development (Li et al. 2021; Song et al. 2018). Therefore, green innovation has been attached importance as the key to solve the conflict between economic growth and resources and environment (Demirel and Kesidou 2011).

Green innovation has "double externalities" (Hall and Helmers 2013; Horbach et al. 2013; Rennings 2000); one is the knowledge spillover externality, that is, the implementing subject of green innovation bears a high innovation cost, but other subjects can obtain green technology at a low cost through imitation and replication, thus reducing the enthusiasm of the green innovation subject. The other is the environmental protection externality, that is, the social benefits brought by environmental protection are greater than the private benefits, resulting in the lack of motivation for green innovation in the private sector. Therefore, it is necessary not only for market demand to stimulate

✉ Yunqiang Liu
liuyunqiang@sicau.edu.cn

Xiaoyu Shao
shaoxiaoyu@stu.sicau.edu.cn

Sha Liu
2020209043@stu.sicau.edu.cn

Ruiping Ran
ranruiping@sicau.edu.cn

[1] College of Management, Sichuan Agricultural University, 211 Huimin Road, Wenjiang District, Chengdu 611130, China

[2] Sichuan Center for Rural Development Research, Chengdu 611130, China

enterprises to provide green products and services but also for environmental regulation to remedy market failure and promote green innovation (Fan et al. 2021). In addition, spatial agglomeration and the spread of environmental pollution may lead to spatial correlation and heterogeneity (Feng et al. 2020; Li et al. 2020; Liu et al. 2020). In open economic environments, different regions can realize innovation through cooperation and resource sharing (Lundberg and Andresen 2012). However, traditional econometric analysis, which is based on spatial irrelevance and homogeneity, can lead to errors in the analysis of regional problems and instability in the results (Su and Yu 2020). Therefore, the impact of environmental regulation and market demand on regional green innovation needs to be examined in a spatial perspective.

There are four main contributions of this study. First, unlike previous studies that have mostly examined the drivers of green innovation at the firm level, this study investigates the impact of both environmental regulation and market demand on green innovation at the regional level, which also provides the possibility to consider spatial spillover effects. Second, the mechanisms by which environmental regulation and market demand affect regional green innovation by changing innovation inputs are assessed. Thirdly, a comprehensive measure of market demand is constructed and calculated using the entropy method to reveal the relationship between market demand and green innovation more accurately. Finally, heterogeneity analysis is performed based on different regions and time periods to propose differentiated green innovation-driven policy insights.

The remainder of this paper is organized as follows: "Literature review" section reviews previous studies; "Theoretical framework and research hypothesis" section details the theory and presents the research hypotheses; "Model setting, variable descriptions, and data sources" section establishes the model and explains the variables and data to be used in the model; "Empirical results and discussion" section empirically examines the influence of environmental regulations and market demand on regional green innovation and the associated mechanisms, conducts a robustness test, and reviews the endogeneity treatment; "Further study" section provides a further analysis by region and time respectively; and "Policy implications and limitations" section gives the conclusions and the possible policy implications.

## Literature review

### Green innovation driving factors

Green innovation research, which was first proposed in the 1990s, mainly refers to green technology innovation, which refers to technologies, processes, or products that can reduce environmental pollution and the use of resources and energy

(Braun and Wield 1994). Green innovation has been seen as similar to environmental innovation, ecological innovation, and sustainability innovation. As the driving factors of green innovation, especially regulatory and market factors, are the focus and core of the study, the existing relevant literatures were vertically combined (Table 1) to visually display the research process and side confirm the marginal contribution of this study.

From the literature review, it can be seen that besides the technology push and market or demand pull factors that influence general innovation, regulations that emphasize the development of new environmentally sound products and processes may also be important green innovation determinants (Horbach 2008). Green innovation driving factors can be summarized using two main approaches, the first of which is to divide it into supply side, demand side, and regulatory factors (Horbach 2008; Triguero et al. 2013). The supply side includes technological capabilities and the ability to cooperate with other innovation subjects to obtain external information and knowledge, the demand side includes market demand and environmental consciousness, and the regulatory factors include policies and subsidies. The second approach is to divide the green innovation factors into internal drivers and external drivers. The internal factors include corporate social responsibility and technological and organizational capabilities, and the external factors include environmental regulations, green customer demand, and the competitive pressures (Cai and Zhou 2014; Kiefer et al. 2019).

### The role of environmental regulation on green innovation

There are three main views on the impact of environmental regulations. First, there is a "cost compliance" effect. Traditional neoclassical economic theory claims that environmental regulation increases enterprise production costs, reduce their profit space, and crowd outs green innovation investment, which inevitably leads to a decline in green innovation efforts (Clarkson et al. 2004; Jaffe and Stavins 1995; Kemp and Pontoglio 2011; Palmer et al. 1995; Testa et al. 2011). The second view is the "innovation compensation" effect. Porter and van der Linde (1995) believed that environmental regulations could force enterprises to actively carry out production technology innovations to reduce costs, improve production efficiency, gain competitive advantage, and offset the negative cost impacts of the environmental regulations (Brunnermeier and Cohen 2003; Feichtinger et al. 2005; Hamamoto 2006). The third view is the "pollution heaven" hypothesis. Due to regional economic development, institutional environment, and factor endowment differences, the effects of environmental regulation policies are not the same (Lin and Du 2015). Furthermore, to attract investment and develop their local economies, some opportunistic and

**Table 1** Literature review of green innovation driving factors

| Authors | Method | Data | Research object | Conclusion |
|---|---|---|---|---|
| Porter and van der Linde (1995) | Qualitative | / | Enterprises | Properly crafted environmental standards can trigger innovation offsets |
| Jaffe and Palmer (1997) | Fixed-effect model | PACE survey | US manufacturing firms | Environmental compliance expenditures had no significant effect on successful patent applications |
| Cleff and Rennings (1999) | Multivariate analysis | Mannheim innovation panel Telephone survey | Germany companies | Environmental product innovation and process innovation are determined by strategic market goals and regulation respectively |
| Brunnermeier and Cohen (2003) | Multivariate analysis | PACE survey | US manufacturing industries | Environmental innovation responded to increases in pollution abatement costs |
| Rehfeld et al. (2007) | Discrete choice models | Telephone survey | German manufacturing | Environmental policy, technology push and market pull have a significant positive influence on environmental product innovations |
| Frondel et al. (2007) | Multinomial logit models | OECD survey | 7 OECD countries | Environmental policies affecting end-of-pipe technologies and clean production are different |
| Horbach (2008) | Binary probit model Multinomial logit model | German panel data | Germany companies | Expected future demand and environmental regulation are important driving forces of environmental innovation |
| Kammerer (2009) | Logit regression | Online-questionnaire | German manufacturers | Customer benefit and regulation play a key role for EP-innovation |
| Demirel and Kesidou (2011) | Tobit model | Government survey | UK manufacturing | Government induced regulations and market factors can effectively promote environmental R&D |
| Horbach et al. (2012) | Binary probit model | Community innovation surveys | Germany companies | Government regulation and customer requirements are particularly important to eco-innovation, and cost savings are important motivation |
| Kesidou and Demirel (2012) | Heckman model | Government survey | UK industry firms | Demand factors affect the decision to undertake eco-innovations, and stricter regulations stimulate the increase of investment |
| Doran and Ryan (2012) | Modified innovation production function | Irish community survey | Irish firms | Regulation and customer perception can explain a firm's decision to engage in eco-innovation |
| Horbach et al. (2013) | Binary probit model | Community innovation surveys | France and Germany firms | Regulation and cost savings play a central role as motivations for eco-innovations |

**Table 1** (continued)

| Authors | Method | Data | Research object | Conclusion |
|---|---|---|---|---|
| Triguero et al. (2013) | Trivariate probit model | Flash Eurobarometer survey #315 | SMEs of 27 European countries | Market share, cost saving and existing regulations have significant positive effects on eco-innovation |
| Cuerva et al. (2014) | Bivariate probit regression | Quantitative analysis | Spanish food and beverage firms | Implementation of voluntary schemes certifications is effective to enhance eco-innovation |
| Cai and Zhou (2014) | Hierarchical regression analysis | Questionnaires and interviews | Chinese firms | Environmental regulations, customers' green demands, and competitors affect eco-innovation through internal drivers |
| del Río et al. (2015) | Bivariate probit model | Technological innovation panel database | Spanish manufacturing firms | Market pull (cost savings) are not a distinctive driver for environmental innovators |
| Ziegler (2015) | Multivariate probit models | Telephone survey | German manufacturing | R&D activities and a few market pull factors have high relevance with technological innovation |
| Costantini et al. (2015) | Negative Binomial Regression Model | BioPat database | Biofuels field of muti-countries | Demand-pull and technology-push factors are found to be important drivers of innovation in the biofuels sector |
| Horbach (2016) | Binary probit models | Community innovation survey | 19 European countries | Regulation subsidies are more important for the Eastern countries than the richer Western European countries |
| del Río et al. (2017) | Dichotomous probit model | Technological innovation panel database | Spanish firms | Cost reductions and environmental regulation influence both products and process eco-innovation |
| Chen et al. (2017) | Panel data model | China Statistical Yearbook | Chinese provinces | Technology push, market pull, and environmental regulation pull have positive influences on the eco-innovation throughout China |
| Cai and Li (2018) | Structural equation model | Questionnaire survey | Chinese firms | Competitive pressures, market-based tools, and customer green demands are conducive to eco-innovation |
| Sanni (2018) | Binary logistic regression | Nigerian innovation survey | Nigerian manufacturing firms | Environmental policy and satisfy customer demands have significant impacts on the decision of firms to eco-innovate |
| Jové-Llopis and Segarra-Blasco (2018) | Dynamic random probit model | Spanish CIS | Spanish manufacturing firms | Public regulations and R&D efforts are the main drivers of enterprise eco-innovation, while market factors are not |
| Kiefer et al. (2019) | Multinomial logistic regression | Questionnaire survey | Spanish industrial SMEs | Technology push and market pull represent drivers to eco innovations |

**Table 1** (continued)

| Authors | Method | Data | Research object | Conclusion |
|---|---|---|---|---|
| Cainelli et al. (2020) | Bivariate probit model | European CIS | 9 European countries | Environmental policy and demand-side factors are both significant in driving the adoption of eco-innovations |
| Fernández et al. (2021) | Multivariate probit models | Four Chilean innovation surveys | Chilean firms | Market factors have a driving effect on eco-innovations |
| Han and Chen (2021) | Multiple regression analysis | Questionnaire survey | Myanmar SMEs | Firm innovation capabilities' positive influence is the most significant predictor of SMEs' eco-innovation in Myanmar |

short-sighted local governments tend to relax their environmental regulations, which form policy depressions (Konisky 2007; Zhao et al. 2020). Consequently, higher polluting industries/enterprises move from areas with stricter environmental regulations to areas with weaker environmental regulations, which results in a pollution heaven in the target area (Cai et al. 2016; Wu et al. 2017).

Some studies have shown that environmental regulations and green innovation policies can have variable impacts on green innovation because of environmental regulation tool heterogeneity (Acemoglu et al. 2012), industry heterogeneity (Aghion et al. 2015b), regional heterogeneity (Chen et al. 2017), and green innovation technology heterogeneity (del Río et al. 2017; Triguero et al. 2013). Other studies have examined the effects of specific environmental regulations, such as renewable energy and carbon market policies, on green innovation (Calel and Dechezleprêtre 2016; Johnstone et al. 2010).

## The role of market demand on green innovation

There has been an ongoing debate as to the effect market demand has on green innovation. Some studies have found that market demand can promote green innovation. For example, using the German Community Innovation Survey data set, Horbach et al. (2012) found that customer requirements were an important eco-innovation source, especially for products that improved environmental performances and process innovations that improve material efficiencies and reduced energy consumption, waste, and hazardous substance use. The personal benefits of green products (such as energy saving) can generate strong consumer demand and incentivize companies to implement green innovations (Kammerer 2009). For example, Veugelers (2012) used data from a Flemish CIS eco-innovation survey, and found that demand-pull was one of the most important motives for eco-innovations.

However, some studies have disagreed with these conclusions. For example, del Río et al. (2017) analyzed the main influencing determinants for different types of eco-innovations in Spain, finding that the market demand-pull had no effect on either process or product eco-innovation, which was seen to be due to the relatively low degree of consumer environmental consciousness and/or the willingness to pay for the higher priced eco-products. Jové-Llopis and Segarra-Blasco (2018) also came to the same conclusion.

From what has been discussed above, existing studies on green innovation driving factors have mostly been focused on more developed countries, such as Spain (del Río et al. 2017; Jové-Llopis and Segarra-Blasco 2018), Germany, and other European countries (Horbach 2016; Triguero et al. 2013), with relatively few studies having been conducted in developing countries. Due to the specific characteristics of each country,

such as the national innovation system, income, and environmental awareness, the green innovation determinants vary widely, which means that the results from one specific country cannot be easily extrapolated to other countries (del Río et al. 2016). In addition, as most studies on the green innovation driving factors have been focused on the enterprise level (Cai and Zhou 2014; Ma et al. 2018), there have been few studies focused on the regional level. Due to the "double externality," the spatial spillover of green innovation and its driving factors differentially affect regional green innovation levels. Chen et al. (2017) examined regional ecological innovation and its influencing factors in China, and specifically studied the impact of technological, market, and environmental regulation on ecological innovation; however, the influencing mechanisms and regional spatial spillovers were not considered. What's more, although existing literatures have studied the spatial spillover effects of environmental regulations, it still lacks of the simultaneous consideration of the spatial effects of policy and market factors on green innovation. Therefore, on the basis of existing research, this study empirically studied the impact of environmental regulations and market demand on green innovation at the regional level, tested the associated mechanisms, and examined the regional spatial spillover effects.

## Theoretical framework and research hypothesis

### Environmental regulations

First, the formula to determine the environmental regulation influence on green innovation was derived. The market demand for green products is assumed to be $d$, the price is $P$, and the output is equal to the demand; therefore, the total revenue is $dp$. The green innovation level is assumed to be $\alpha$, and the pollutant emissions related to the green innovation level and product output are expressed as $e(\alpha, d)$, where $e'(\alpha) < 0, e'(d) > 0$. The unit pollutant environmental costs, such as the pollutant charges and the environmental pollution control investment, are $k$; therefore, the total environmental costs are $ke(\alpha, d)$. The green technology innovation cost is expressed as $I(\alpha)\big(I'(\alpha) > 0\big)$; therefore, the profit can be expressed as:

$$\pi = TR - TC = dp - ke(\alpha, d) - I(\alpha) \tag{1}$$

Taking the derivative of Eq. (1) and setting it to 0, then:

$$k = -\frac{I'(\alpha)}{e'(\alpha, d)} \tag{2}$$

It is assumed that the green technology in region $i$ is upgraded, and the green innovation level increases to $\alpha_i$,

if the profit increases after the green innovation, the region would choose to upgrade their technology.

The original profit in region $i$ would be:

$$\pi_0 = dp - ke_0(d) \tag{3}$$

and the profit after the green technology upgrade would be:

$$\pi_i = dp - ke_i(\alpha_i, d) - I(\alpha_i) \tag{4}$$

Therefore, the change in the profit would be:

$$\Delta\pi = k\big(e_0(d) - e_i(\alpha_i, d)\big) - I(\alpha_i) \tag{5}$$

This profit change depends on two parts; if the environmental costs saved by the pollution reductions from the green technology upgrade are no less than the cost of the investment required for the green technology upgrade, the green innovation is implemented.

Taking the partial derivative of $k$ with respect to Eq. (5):

$$\frac{\partial \Delta\pi}{\partial k} = e_0(d) - e_i(\alpha_i, d) - I'(\alpha_i)\frac{\partial \alpha_i}{\partial k} \tag{6}$$

and then setting Eq. (6) to 0, then:

$$\frac{\partial \alpha_i}{\partial k} = \frac{e_0(d) - e_i(\alpha_i, d)}{I'(\alpha_i)} \tag{7}$$

When combined with Eq. (2), when $e_0(d) > e_i(\alpha_i, d)$ $(k_i > -\frac{I'(\alpha)}{e'(\alpha, d)})$, $\frac{\partial \alpha}{\partial k} > 0$, when $e_0(d) < e_i(\alpha_i, d)(k < -\frac{I'(\alpha)}{e'(\alpha, d)})$, $\frac{\partial \alpha_i}{\partial k} < 0$, and when $e_0(d) = e_i(\alpha_i, d)$, $\frac{\partial \alpha_i}{\partial k} = 0$. The critical value for the per unit pollutant environmental costs in region $i$ is assumed to be $\hat{k}$. When $k < \hat{k}$, the green innovation level $\alpha_i$ decreases with an increase in $k$, and when $k > \hat{k}$, the green innovation level $\alpha_i$ increases with an increase in $k$.

Studies have shown that the environmental regulation impact on technological innovation is a result of both positive and negative effects. The "cost compliance" effect usually occurs in the current period, while the "innovation compensation" effect has a time lag and can only emerge over the long term (Horváthová 2012; Lanoie et al. 2008). In other words, when the environmental regulation policy intensity is weak, because of the "cost compliance" effect, the increased costs crowd out the innovation input, which is not conducive to enterprise green innovation. As the environmental regulation policy intensity increases, because of the "innovation compensation" effect, enterprises gradually obtain greater benefits from the green innovation to offset the increased environmental costs (Ouyang et al. 2020). Therefore, based on this discussion, the following hypothesis is proposed.

*Hypothesis 1.* There is a U-shaped relationship between environmental regulation and green innovation, that is, at a low-level initial period, an increase in the environmental regulation policy intensity reduces the green innova-

tion ability; however, when it reaches a certain level, an increase in the environmental regulation policy intensity promotes an improvement in the green innovation ability.

The environmental regulation effects on surrounding areas need to be analyzed from a local government behavior perspective, which has been identified as a "race to the bottom" or a "race to the top." Bu and Wagner (2016) analyzed the American multinational foreign direct investment in China and found that some companies had the ability to invest in areas with stricter environmental regulations, but companies that were unable to cope with the environmental pollution penalties were less likely to target these areas, with this impact being found to be moderated by enterprise scale, that is, there was a "race to the bottom" based on a "pollution heaven" and a "race to the top" based on innovation induction theory. On a more practical level, to attract investment, some local governments relax the environmental regulations, that is, they encourage a "race to the bottom" based on a "pollution heaven." Other local officials may seek fame or promotion because of their environmental governance achievements, that is, they encourage a "race to the top" by improving their environmental regulations. Holzinger and Sommerer (2011) studied 24 European countries and found that local governments had "race to the top" environmental regulation features. Therefore, both a "race to the bottom" and a "race to the top" can result in environmental regulation changes and affect the regional green innovation levels. Based on this discussion, the following hypothesis is proposed:

*Hypothesis 2*. Local environmental regulations have a significant impact on the green innovation level in surrounding areas.

## Market demand

The formula for the market demand influence on green innovation is then derived. Taking the partial derivative for $d_i$ with respect to Eq. (5):

$$\frac{\partial \Delta \pi}{\partial d} = k(e_0'(d) - e_i'(\alpha_i, d)) - I'(\alpha_i)\frac{\partial \alpha_i}{\partial d} \tag{8}$$

Then setting Eq. (8) to 0;

$$\frac{\partial \alpha_i}{\partial d} = \frac{k(e_0'(d) - e_{i1}'(\alpha_i, d))}{I'(\alpha_i)} \tag{9}$$

When $e_0'(d) - e_i'(\alpha_i, d) > 0$ and $k > 0$, $I'(\alpha_i) > 0$ and $\frac{\partial \alpha_i}{\partial d} > 0$, that is, with an increase in the green market demand $d$, the green innovation level $\alpha_i$ also increases.

Theoretically, market demand provides clear goals for green innovation and reduces uncertainty because

enterprises pay closer attention to their consumers' needs and innovate new products and services accordingly to gain competitive advantage (Varadarajan 2020). Market demand can also improve the expected returns from green products and services and provide the internal impetus for green innovation. As economies develop, public consumption and environmental protection awareness increases, which means that they are more inclined to buy green products and services (Albort-Morant et al. 2016). As the market demand for green technologies has been increasing, the level of green innovation has also been increasing; therefore, the following hypothesis is proposed:

*Hypothesis 3*. Green innovation is influenced by market demand; therefore, as the market demand for green technology increases, the level of green innovation also increases.

Market demand refers to the demand by consumers that have both the desire and the ability to buy, that is, market demand depends on people. Because of major developments in transportation, communication, and other infrastructure, the time distance between regions has become shorter, communication deeper, and consumer mobility enhanced (Tang et al. 2021). Therefore, because of this population mobility, the increased regional market demand can enhance the consumption and green consumption awareness of consumers in surrounding areas, which is known as the "ripple" effect (Dong et al. 2020; Zhu and Lee 2021), which then motivates green innovation in the surrounding areas. However, an increase in the regional market demand could also lead to many green innovations, which would need resources from the surrounding area, which in turn would reduce the green innovation and result in a "siphon" effect (Su et al. 2021). As any changes in the regional market demand impact surrounding areas because of the prevalence of agglomeration and diffusion effects, the following hypothesis is proposed:

*Hypothesis 4*. Local market demand has a significant impact on the green innovation in the surrounding areas.

## Mechanism analysis

The environmental regulation "compliance cost" and "innovation compensation" effects on the environmental regulation mechanism and green innovation is analyzed in this section. First, environmental regulations inhibit regional innovation input, that is, neoclassical economic theory claims that environmental regulations increase enterprise environmental costs, which can result in product price increases and a decline in product competitiveness, and if the product price is not increased, the profit is significantly reduced, which also negatively impacts market

**Fig. 1** Conceptual model
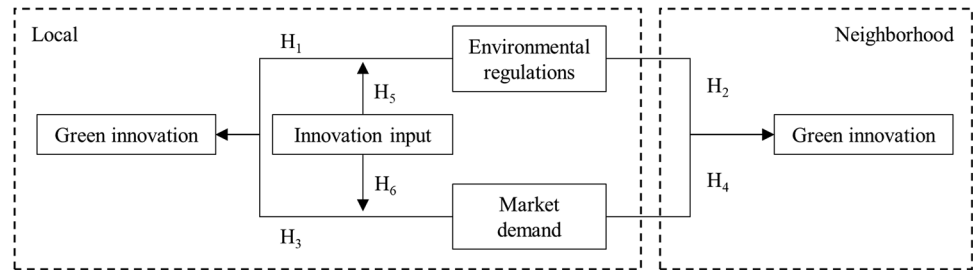


competitiveness. Any weakening of competitiveness reduces cash flow, and any increase in enterprise costs reduces the availability of new product research and development funds and make it difficult to finance innovation activities through other channels. In a study on European chemical industry enterprises, Arduini and Cesaroni (2001) found that excessive environmental regulations were negatively correlated with technological innovation input. Gray and Shadbegian (2003) found that the legal regulations in the USA that required enterprise pollution control investment almost completely crowded out any productive investment in the pulp and paper industry. Kneller and Manderson (2012) found that environmental regulation had no significant impact on total R&D and total capital accumulation based on the British manufacturing industry. Rubashkina et al. (2015) found that environmental regulations had an insignificant crowding out effect on R&D investment. Second, environmental regulations can promote regional innovation input. The "Porter hypothesis" claims that companies will actively invest in innovation activities to offset the additional environmental regulation compliance costs and enhance competitiveness. Chakraborty and Chatterjee (2017) found that environmental regulation significantly increased innovation spending in India's leather and textile industries. Costa-Campi et al. (2017) studied Spanish manufacturing industry and found that environmental regulation had an incentive effect on environmental R&D investment. Yu and Cheng (2021) studied listed textile companies in China and found that environmental taxes effectively promoted enterprise innovation investment.

Similarly, the increased market demand for new products or services also affects regional innovation investment. In a study on China's home appliance industry, Lv and Huang (2021) found that the expansion in the home appliance market significantly improved innovation input. Garcia-Quevedo et al. (2017) study the innovation data of Spanish enterprises and find that lack of demand not only has a significant negative impact on the amount of R&D investment but also on the possibility of enterprises engaging in R&D activities. Positive expectations of adequate market demand are a necessary condition for deciding to invest in R&D (Barge-Gil and López 2014, 2015; García-Quevedo et al. 2014). Large market demand scale can reduce green innovation

uncertainty and generate profit expectations, which then motivate internal green innovation. Therefore, enterprises, universities, research institutions, and other innovation subjects tend to increase their green innovation investments to obtain green innovation results and enhance their green innovation levels.

The increase in regional innovation inputs can improve green innovation levels. Studies have shown that environmental R&D investment directly promotes environmental technology innovation (Li et al. 2019). Specifically, Hashi and Stojčić (2013) found that investment in innovative activities could increase sales of new products. By studying energy industry, food and beverage industry in Spain and manufacturing industry in France and the Netherlands, Costa-Campi et al. (2014), Acosta et al. (2015), and Raymond et al. (2015) respectively found that R&D intensity and expenditure have a significant effect on process innovation, product innovation, and organizational innovation. Frank et al. (2016) believed that market-oriented R&D activities had a positive impact on innovation output. Therefore, based on this discussion, the following hypothesis is proposed:

> *Hypothesis 5*. Environmental regulation affects regional green innovation through changes in the innovation input.
> *Hypothesis 6*. An increase in market demand leads to a corresponding increase in innovation input, which then promotes regional green innovation.

Therefore, environmental regulations and market demand affect green innovation in the local and neighboring regions, with this local green innovation being influenced by innovation input. The conceptual model for this supposition is shown in Fig. 1.

## Model setting, variable descriptions, and data sources

### Model building

Griliches (1979) proposed a knowledge production function based on the Cobb–Douglas production function to describe

the relationship between a certain combination of production factors that were invested in knowledge production and output, which has been widely used and improved in subsequent technological innovation studies (Griliches [1984](); Jaffe [1986]()). The mathematical expression for this knowledge production function is:

$$Y = AK^a L^b \tag{10}$$

where $Y$ is the knowledge output level, which is usually represented by the number of patents, $K$ and $L$ are the capital and labor force inputs in the technological innovation activities, and $A$ is the other factors affecting the knowledge production. To eliminate the data stability influence of heteroscedasticity and extreme values, natural logarithms are taken from both the left and right sides of the formula to obtain:

$$\ln Y = C + a \ln K + b \ln L + u \tag{11}$$

For the empirical model in this study, environmental regulations, market demand, and the environmental regulation quadratic were introduced into the formula, with the related explanatory variables being controlled. As green innovation output is largely dependent on the output in the previous period because of path dependence and cumulative effects (Aghion et al. [2012]()), a first-order green innovation lag, $GI_{i,t-1}$, was introduced into Eq. ([12]()) as an explanatory variable, which also resolved the endogeneity problem caused by the missing variables.

$$
\begin{aligned}
\ln GI_{it} = {} & \alpha_0 + \alpha_1 \ln GI_{i,t-1} + \alpha_2 \ln ER_{it} + \alpha_3 \ln MD_{it} \\
& + \alpha_4 \ln ER_{it}^2 + \lambda \ln X_{it} + u_i + v_t + \varepsilon_{it}
\end{aligned} \tag{12}
$$

where $ER$ is the environmental regulations, $MD$ is the market demand, $ER^2$ is the environmental regulation quadratic used to test whether there is a U-shaped relationship between environmental regulation and green innovation, $X$ is the control variable that represents the other factors that affect green innovation, $\alpha$ and $\lambda$ are the estimated parameters, $u_i$ and $v_t$ are individual and time effects, $\varepsilon_{it}$ is the random error, $i$ represents the regions, and $t$ represents the year.

The above model only considers the environmental policy impact, market demand, and other factors on local green innovation. As green innovation has obvious agglomeration and spillover effects, the correlation effects between regions should also be considered. Therefore, following Elhorst ([2012]()), the model was further expanded to a dynamic spatial econometric model. As the variables were all ratios, the logarithm was not taken.

$$
\begin{aligned}
GI_{it} = {} & \alpha_0 + \delta W \cdot GI_{i,t} + \alpha_1 GI_{i,t-1} + \sigma_1 W \cdot GI_{i,t-1} + \alpha_2 ER_{it} + \alpha_3 MD_{it} + \alpha_4 ER_{it}^2 + \\
& \sigma_2 W \cdot ER_{it} + \sigma_3 W \cdot MD_{it} + \sigma_4 W \cdot ER_{it}^2 + \lambda X_{it} + \gamma W \cdot X_{it} + u_i + v_t + \xi_{it}
\end{aligned} \tag{13}
$$

where $W$ represents the spatial weight matrix. The geographical distance space weight matrix $W_1$, the economic distance space weight matrix $W_2$, and the nesting geographic and economic distance matrix $W_3$ were used. The geographical distance space weight matrix was $W_1 = 1/d_{ij}$, in which $d_{ij}$ was the longitude and latitude distances between capital cities. The economic distance space weight matrix was $W_2 = 1/\left|\overline{G}_i - \overline{G}_j\right|$, $\overline{G}_i$, and $\overline{G}_j$ respectively represented the average GDP per capita from 2006 to 2020 of provinces $i$ and $j$. The nesting geographic and economic distance matrix was $W_3 = \varphi W_1 + (1 - \varphi) W_2$ (Case et al. [1993]()). To simplify the analysis, $\varphi$ was set to 0.5. All three matrixes were row standardized.

To test the environmental regulation and market demand mechanism affecting green innovation, based on Baron and Kenny ([1986]()), first, the effects of the environmental regulation and market demand on green innovation were analyzed. Then, the effects of the environmental regulation and market demand on the innovation input were considered. Finally, the effects of the innovation input, environmental regulation, and market demand on the green innovation were tested. The model constructed in the first step was the same as the basic regression in Eq. ([13]()), and the second and third steps are expressed in Eqs. ([14]()) and ([15]()).

$$
\begin{aligned}
RD_{it} = {} & \eta_0 + \lambda W \cdot RD_{i,t} + \eta_1 RD_{i,t-1} + \theta_1 W \cdot RD_{i,t-1} + \eta_2 ER_{it} + \eta_3 MD_{it} + \eta_4 ER_{it}^2 + \\
& \theta_2 W \cdot ER_{it} + \theta_3 W \cdot MD_{it} + \theta_4 W \cdot ER_{it}^2 + \omega X_{it} + \psi W \cdot X_{it} + u_i + v_t + \tau_{it}
\end{aligned} \tag{14}
$$

$$
\begin{aligned}
GI_{it} = {} & \beta_0 + \zeta W \cdot GI_{i,t} + \beta_1 GI_{i,t-1} + \rho_1 W \cdot GI_{i,t-1} + \beta_2 ER_{it} + \beta_3 MD_{it} + \beta_4 ER_{it}^2 \\
& + \beta_5 RD_{it} + \rho_2 W \cdot ER_{it} + \rho_3 W \cdot MD_{it} + \rho_4 W \cdot ER_{it}^2 + \rho_5 W \cdot RD_{it} \\
& + \kappa X_{it} + \chi W \cdot X_{it} + u_i + v_t + \varepsilon_{it}
\end{aligned} \tag{15}
$$

Where $RD$ refers to the innovation input, which was measured by the ratio of actual R&D internal expenditure and regional GDP (Chen et al. [2021]()). The actual R&D internal expenditure needed to be deflated by the R&D expenditure price index. $\eta$, $\theta$, $\omega$, $\psi$, $\beta$, $\rho$, $\kappa$, and $\chi$ were the parameters to be estimated, and $\tau_{it}$ and $\varepsilon_{it}$ were the random errors.

## Variable selection and processing

### Dependent variable: green innovation (*GI*)

Regional innovation is often measured by the number of patents and the revenue from new product sales. As it was difficult to obtain the sales income for the regional green products, the "IPC Green Inventory" published by the World Intellectual Property Organization (WIPO) in 2010 was consulted to provide the green patent data. The international patent classification numbers on the list were searched on the Patent Information Service platform of the Intellectual Property Office of the People's Republic of China and sorted by address and grant date. The reason the number of green

patent grants was used instead of the number of applications was that the number of examined patent grants better reflects the true innovation level. Regional green innovation was finally measured based on the number of green granted patents per 10,000 people. The per capita number of green patents was used as it excludes the influence of the regional populations.

### Independent variables

**Environmental regulation (*ER*)** Environmental regulation intensity can be measured based on pollution control investment (Becker 2005), pollutant emissions (Smarzynska and Wei 2004), natural policy experiments (Greenstone 2002), and a comprehensive evaluation method. Based on data availability, the ratio of total waste water discharge to industrial output value, the ratio of sulfur dioxide discharge to industrial output value, and the comprehensive utilization rate of industrial solid waste were selected. The entropy method was used to construct comprehensive indicators to measure the environmental regulation, with the first two being negative indicators and the third being positive. The scientific characteristics of this measure were as follows. Three industrial pollutants, waste water, waste gas, and solid waste, were chosen to comprehensively reflect the discharge/use of each pollutant, and the ratio of the pollutant discharges to the total industrial output value adopted to account for the regional industrial production scale and ensure comparability. The gross industrial output value was deflated using the industrial producer price index, with 2006 being the base period. The entropy method steps to construct the comprehensive environmental regulation indicators were as follows:

First, the data were positively normalized:

$$E_{ij}^* = \frac{E_{ij} - min(E_j)}{max(E_j) - min(E_j)} \tag{16}$$

where $E_{ij}$ was the measurement for pollutant $j$ in region $i$ in the year, $min(E_j)$ and $max(E_j)$ were the minimum and maximum values for $j$ pollutant in all regions, and $E_{ij}^*$ was the normalized value.

Second, the entropy value for pollutant $j$ was calculated as follows:

$$g_j = -\frac{1}{\ln n} \sum_{i=1}^{n} f_{ij} \ln f_{ij}, f_{ij} = \frac{E_{ij}^*}{\sum_i^n E_{ij}^*} \tag{17}$$

Third, the index weight was determined:

$$h_j = (1 - g_j) \Big/ \sum_{j=1}^{3} (1 - g_j) \tag{18}$$

Finally, the environmental regulation intensity was obtained using weighting:

$$ER_i = \sum_{j=1}^{3} h_j f_{ij} \tag{19}$$

**Market demand (*MD*)** To measure market demand, existing studies have mostly use Community Innovation Survey data, obtained data from questionnaires, telephone surveys, or interviews, or used single indicators such as per capita income (Cai and Zhou 2014; Chen et al. 2017; Horbach et al. 2012; Kammerer 2009; Ziegler 2015), which are relatively single and difficult to accurately reflect the "green" elements.

Considering the expected market demand, the public awareness of environmental protection, and the public preference for environmentally friendly products (Horbach 2008), based on the availability of data, the green technology market demand measurement index system was constructed using per capita domestic energy consumption, per capita domestic carbon dioxide emissions, per capita domestic water consumption, per capita domestic garbage delivery quantity, per capita public transport times, per capita disposable income, and public environmental awareness, with the first four being negative indicators and the last three being positive indicators.

The original domestic energy consumption data were taken from the domestic consumption sections of the regional energy balance tables and were converted into standard coal and summed. The domestic carbon dioxide emissions were calculated using the IPCC greenhouse gas emissions calculation method (Wu et al. 2021b). Similarly, the entropy value method was used to calculate the index weight, which was then used to determine the market demand.

**Control variables** Four indicators, government support, trade openness, infrastructure construction, and intellectual property protection, were selected as the control variables.

Government support (*GS*): environmental policies that affect green innovation such as the various incentives offered in addition to the regulatory measures. Horbach (2008) found that subsidies had a significant positive impact on environmental product innovation; therefore, it was necessary to control the influence of this factor.

Trade openness (*TO*): opening to the outside world is conducive to attracting foreign-funded enterprises with higher energy saving and emissions reduction technologies to conduct green production activities, which improves the regional green innovation levels. However, in developing countries with lower environmental standards, higher

**Table 2** Variable measurements

| Variable types | Variables | Symbol | Measure |
|---|---|---|---|
| Dependent variable | Green innovation | *GI* | Number of green granted patents per 10,000 people |
| Independent variables | Environmental regulation | *ER* | Ratio of total waste water discharge to industrial output value |
| | | | Ratio of sulfur dioxide discharge to industrial output value |
| | | | Comprehensive utilization rate of industrial solid waste |
| | Market demand | *MD* | Per capita domestic energy consumption |
| | | | Per capita domestic carbon dioxide emissions |
| | | | Per capita domestic water consumption |
| | | | Per capita domestic garbage delivery quantity |
| | | | Per capita public transport commute times |
| | | | Per capita disposable income |
| | | | Average school years |
| Control variables | Government support | *GS* | Proportion of expenditure on science and technology |
| | Trade openness | *TO* | Ratio of total imports and exports to regional gross domestic product |
| | Infrastructure construction | *IC* | Length of long-distance cable per unit area |
| | Intellectual property protection | *IPR* | Ratio of technology market turnover to regional gross domestic product |

polluting enterprises may enter, thus causing a "pollution heaven" effect, which is not conducive to regional green innovation.

Infrastructure construction (*IC*): regional green innovation relies on high-quality talent and complete transportation infrastructure with fast commuting speeds, which save time and costs. As talent is also an important carrier of knowledge and technology spillover, improvements in communication, the internet, and other infrastructure can significantly increase the frequency and efficiency of communication and promote further regional green innovation improvements.

Intellectual property protection (*IPR*): the intellectual property protection level reflects the legal protection given to green technology innovation and therefore plays an important role in green innovation. As the green innovation subjects are rational people, they implement green innovation only when they can get guaranteed returns (Horbach 2008). As the creator of the asset usually does not receive all or even most of the social returns generated (Jaffe et al. 2002), innovation agents tend to minimize spillovers as much as possible. Therefore, green innovation can be affected by the degree of intellectual property protection being offered.

The specific measurement methods for the dependent, independent, and control variables are shown in Table 2.

## Data sources

Panel data for 30 provinces/autonomous regions/municipalities (Tibet was not included due to missing data) in mainland China from 2006 to 2020 were used. The green patent data were obtained by manually searching and summarizing the information from the China National Intellectual Property

Administration and referring to the "IPC Green Inventory." Other data came from the China Statistical Yearbooks, the China City Statistical Yearbooks, the China Energy Statistical Yearbooks, and the China Environment Statistical Yearbooks. Data for all currency values were at 2006 constant prices. The descriptive statistics for each variable are shown in Table 3.

## Empirical results and discussion

### Spatio-temporal green innovation evolution

(1) Changes at the time level

It can be seen from Fig. 2 that, from 2006 to 2013, the number of green patent grants in various regions of China increased significantly, and in some regions, it increased

**Table 3** Descriptive variable statistics

| Variables | Average | Standard deviation | Minimum | Maximum | Observation number |
|---|---|---|---|---|---|
| *GI* | 0.125 | 0.199 | 0.000 | 1.644 | 450 |
| *ER* | 0.033 | 0.011 | 0.008 | 0.073 | 450 |
| *MD* | 0.033 | 0.029 | 0.008 | 0.184 | 450 |
| *GS* | 0.02 | 0.014 | 0.004 | 0.072 | 450 |
| *TO* | 0.295 | 0.355 | 0.008 | 1.799 | 450 |
| *IC* | 0.183 | 0.129 | 0.019 | 0.893 | 450 |
| *IPR* | 0.013 | 0.025 | 0.000 | 0.175 | 450 |

**Fig. 2** Green innovation levels in 2006, 2013, and 2017
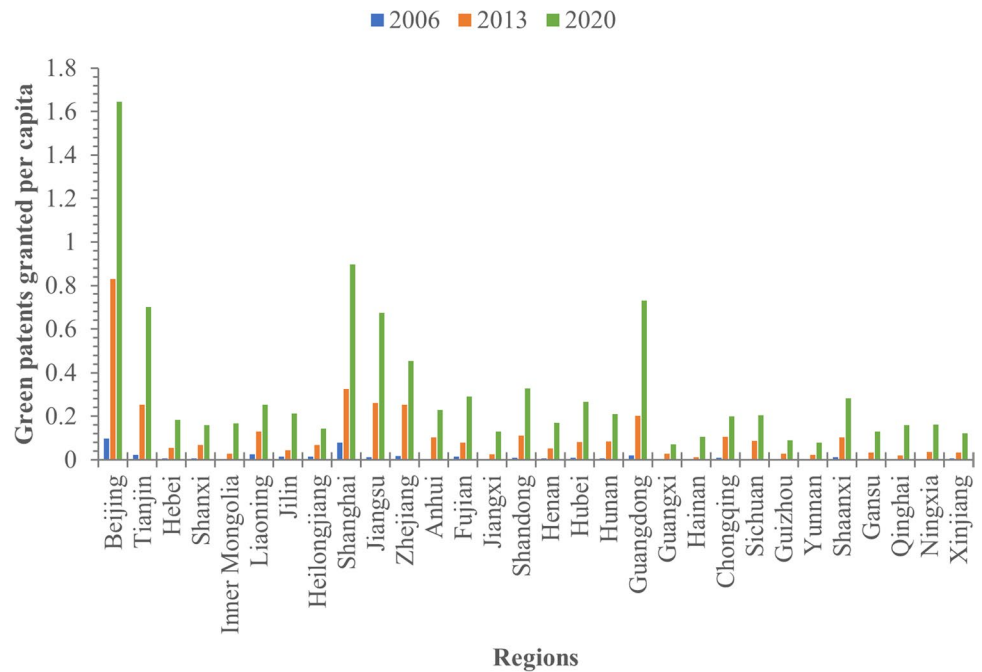


significantly from nearly 0. The fifth Plenary Session of the 16th Central Committee of the Communist Party of China (held in October 2005) and the 17th National Congress of the Communist Party of China (held in October 2007) proposed to accelerate the transformation of the economic growth mode, from the "extensive" mode with high consumption and cost to the "intensive" mode with low consumption and cost (Tang et al. 2020). Therefore, most regions began to improve the utilization efficiency of resources through technological innovation.
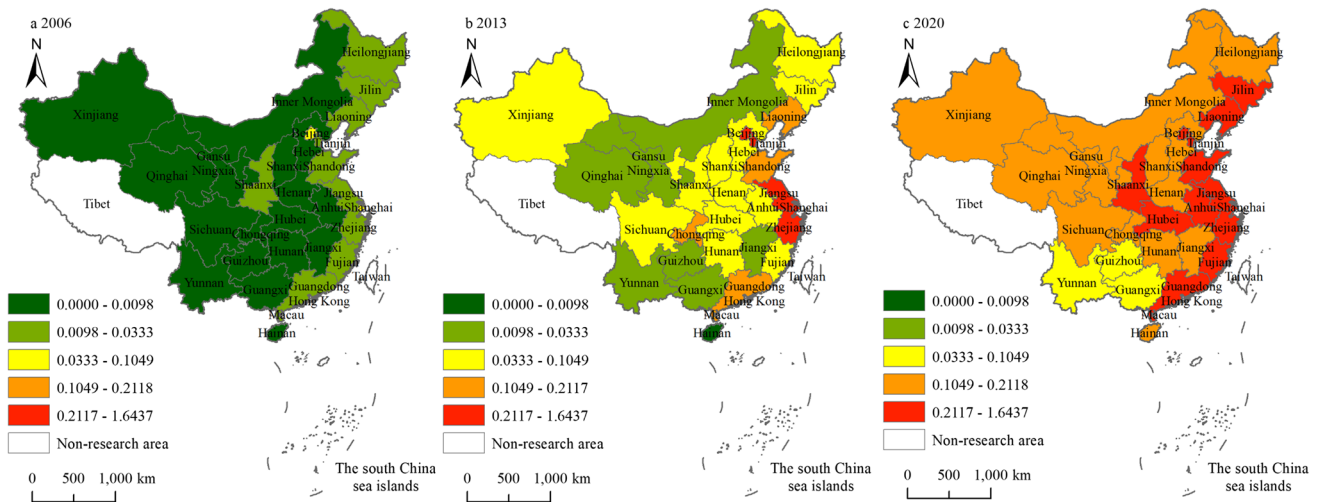
From 2013 to 2020, the level of green innovation in all regions of China has further improved, with the number of green patents granted per 10,000 people in Beijing, Tianjin, Shanghai, Jiangsu, and Guangdong exceeding 0.6. The Kyoto Protocol stipulated those developing countries undertake emission reduction obligations from 2012, and the fifth Plenary Session of the 18th CPC Central Committee (held in October 2015) proposed the concept of green development (Pan et al. 2019), which was not only the inheritance of sustainable development theory but also the theoretical innovation of sustainable development in China. Under such policies, the level of green innovation in all regions of China has significantly improved.

(2) Changes at the spatial level

In order to analyze the spatial distribution and evolution characteristics of regional green innovation, the green innovation level in 2006, 2013, and 2020 were presented by quantile method, as shown in Fig. 3. In 2006, the level of green innovation in Beijing was the highest. As the capital

of China, Beijing is the center of scientific and technological innovation, bringing together a large amount of knowledge and talents, thus leading the development of green innovation in China. As a result of the opening up, most eastern regions experienced rapid economic development, so they started green innovation exploration earlier. However, due to the remote geographical location, most inland regions in central and western China still adopt extensive economic development mode, so the level of green innovation was close to 0.

In 2013, the classification characteristics of regional green innovation were obvious, and The Beijing-Tianjin region and Yangtze River Delta region took the lead in green innovation level. As the two major economic circles in China, they have a high level of economic development, so they can take the lead in transforming the economic development mode and making more efficient use of resources, and the green innovation level be improved accordingly. Then, it was followed by green innovation in Guangdong, Liaoning, Shandong, and Chongqing. The Pearl River Delta in Guangdong province is the third largest economic circle in China, and Liaoning and Shandong belong to the Bohai Rim economic region, and Chongqing is one of the four municipalities directly under the central government in China. Their geographical location and administrative level make them also have a relatively rapid speed of green innovation development. All provinces except Hainan got rid of the lowest level of green innovation, which is because Hainan, an island, mainly develops tourism due to its unique natural landscape and climatic conditions,

**Fig. 3** Spatio-temporal green innovation distribution

and therefore has a low level of green innovation which is closely related to manufacturing.

In 2020, the green innovation level of most provinces has been upgraded to the top two levels, with only Guizhou, Yunnan, and Guangxi in the west lagging behind. The reason might be that these provinces were remote and poor, which were difficult to attract high-quality talents and lacked innovation resources, resulting in low green innovation level.

## Spatial correlation test and econometric model selection

First, a spatial correlation test for the explained green innovation variable was conducted to verify the need to adopt the spatial econometric model. In empirical studies, Moran's I index has been more commonly used to investigate the spatial correlation of variables, with its value being between − 1 and 1, with a significantly positive value indicating a spatial positive correlation and a significant negative value indicating a spatial negative correlation. The Moran' I of green innovation from 2006 to 2020 under three spatial weight matrixes is shown in Table 4, with the results showing that the Moran's I index was significant from 2006 to 2020, which indicated that the explained variables had obvious spatial positive correlations and it was necessary to establish a spatial econometric model to investigate the problem. Compared with geographical distance weight matrix, the correlation under economic distance weight matrix is stronger, indicating that economic proximity is more conducive to the spatial spillover of green innovation.

As there are many spatial econometric models, it was necessary to select the most appropriate. The (Robust) LM test, Wald test, and LR test were therefore successively conducted, and the results from which are shown in Table 5.

First, the OLS estimation was carried out on the non-spatial panel data model, from which it was found that the LM test and robust LM test results significantly rejected the null hypothesis for the explained variable without any spatial lag and spatial autocorrelation error regardless of whether the temporal and spatial fixed effects were included. Second, a likelihood ratio (LR) test was conducted to judge whether there were any time fixed or spatial fixed effects, and the test results rejected the joint non-significant null hypothesis for time and spatial fixed effects, the model with time and spatial fixed effects should have been be adopted; however, LeSage and Pace (2009) pointed out that the Wald and LR tests should still be used to determine whether the spatial Durbin model could be reduced to a spatial lag model and a spatial error model. The results showed that the Wald test and LR test rejected the null hypothesis, and the spatial Durbin model better fit the data. Therefore, the spatial Durbin model (SDM) with both time and spatial fixed effects was finally chosen as the estimation model, and mainly focused on the estimation results under the economic distance weight matrix.

## Basic regression results and discussion

To compare and test the necessity and reliability of introducing the dynamic spatial econometric model, the estimation results for the non-spatial fixed effects model and the static and dynamic SDM with time and space fixed effects under three spatial weight matrixes are given in Table 6.

The $R^2$ and log-likelihood values indicated that compared with non-spatial fixed effects model and static SDM model, the dynamic SDM had stronger explanatory power, and the dynamic SDM under the economic distance weight matrix was the strongest, which was used as the benchmark model

**Table 4** Spatial correlation test results for the explained variable

| Year | W₁ | | W₂ | | W₃ | |
|---|---|---|---|---|---|---|
| | Moran's I | Z value | Moran's I | Z value | Moran's I | Z value |
| 2006 | 0.021* | (1.894) | 0.876*** | (9.497) | 0.448*** | (9.623) |
| 2007 | 0.061*** | (3.278) | 0.809*** | (8.851) | 0.435*** | (9.411) |
| 2008 | 0.077*** | (3.490) | 0.828*** | (8.248) | 0.453*** | (8.892) |
| 2009 | 0.066*** | (3.478) | 0.790*** | (8.760) | 0.428*** | (9.383) |
| 2010 | 0.086*** | (3.935) | 0.760*** | (7.958) | 0.423*** | (8.748) |
| 2011 | 0.061*** | (3.160) | 0.822*** | (8.626) | 0.442*** | (9.160) |
| 2012 | 0.071*** | (3.542) | 0.714*** | (7.717) | 0.393*** | (8.405) |
| 2013 | 0.054*** | (3.345) | 0.508*** | (6.307) | 0.281*** | (7.007) |
| 2014 | 0.040*** | (3.235) | 0.468*** | (6.765) | 0.254*** | (7.424) |
| 2015 | 0.043*** | (3.258) | 0.467*** | (6.479) | 0.255*** | (7.155) |
| 2016 | 0.061*** | (3.749) | 0.529*** | (6.813) | 0.295*** | (7.613) |
| 2017 | 0.072*** | (3.820) | 0.532*** | (6.253) | 0.302*** | (7.092) |
| 2018 | 0.052*** | (3.016) | 0.531*** | (6.019) | 0.292*** | (6.631) |
| 2019 | 0.049*** | (2.916) | 0.522*** | (5.981) | 0.285*** | (6.566) |
| 2020 | 0.065*** | (3.279) | 0.631*** | (6.682) | 0.348*** | (7.338) |

Values in brackets are Z values, ***, **, and * respectively represent significance at 1%, 5%, and 10% levels

for the empirical analysis. In the dynamic SDM estimation, the spatial lag parameter green innovation estimations were all significantly positive, which indicated that green innovation had a positive interaction or correlation effect in space, and that a large number of regions with high level green innovation were clustered around the regions with rapid green innovation developments. The parameter estimations for the phase 1 green innovation lag were all significantly positive, indicating that there was a significant cumulative effect of green innovation over time, and the green innovation in the last phase had a co-acting effect on the current phase (Jové-Llopis and Segarra-Blasco 2018). The spatial lag parameter estimations of the phase 1 green innovation lag were all significantly negative, indicating that the local green innovation in the last phase had a negative spatial correlation effect on the neighborhood green innovation. Many green innovation resources were in the regions with higher green innovation levels in the last phase, indicating that there had been "siphonic effect" on current green innovation in the surrounding areas. It should be noted that the impacts of market demand on green innovation in non-spatial FE model and static SDM model were opposite to that in dynamic SDM model. Without considering the development level of the previous phase, the overall market demand presents a downward trend, while the level of green innovation keeps improving, so the effect of market demand on green innovation was negative. However, the dynamic SDM model took the time path dependence into account, so its results can show the real relationship between market demand and green innovation, that is, market demand could promote the improvement of local green innovation level, which was also the reason why the dynamic SDM model was adopted.

The spatial spillover effect of the dynamic SDM showed a global effect, and the point estimation results for which did not represent the marginal impact of the explanatory variables. Therefore, because of the point estimation results, the direct effect, indirect effect, and total effect of each explanatory variable needed to be further measured (Elhorst 2014; LeSage and Pace 2009). The results are shown in Table 7.

(1) Environmental regulation

The direct effects of environmental regulation were significantly negative under three spatial weight matrixes, while the direct effects of its quadratic were significantly positive which indicated that the environmental regulation effect on local green innovation satisfied the positive U-shaped relationship, confirming $H_1$. In the short term, the environmental regulations mean that the enterprises need to pay extra costs for pollution, which squeezes the funds available for green innovation and is not conducive to the development of regional green innovation. As the environmental regulations are strengthened, the cost of meeting the environmental protection requirements increases, which means that the enterprises can obtain greater benefits through green innovation, which reduces the pollution emissions and environmental costs and enhances competitive advantage through the differentiated green products and services.

**Table 5** Selection of spatial econometric model

| Weight matrixes | Test methods | Joint OLS | Spatial fixed effect | Time fixed effect | Spatial and time fixed effect | Test methods | Spatial panel model |
|---|---|---|---|---|---|---|---|
| $W_1$ | LM-spatial lag | 123.107*** | 91.870*** | 2.892* | 0.003 | Wald-spatial lag | 26.722*** |
| | | [0.000] | [0.000] | [0.089] | [0.957] | | [0.000] |
| | Robust LM-spatial lag | 69.623*** | 49.134*** | 7.261*** | 6.494** | LR-spatial lag | 33.702*** |
| | | [0.000] | [0.000] | [0.007] | [0.011] | | [0.000] |
| | LM-spatial error | 64.875*** | 82.256*** | 0.248 | 5.628** | Wald-spatial error | 24.920*** |
| | | [0.000] | [0.000] | [0.618] | [0.018] | | [0.000] |
| | Robust LM-spatial error | 11.391*** | 39.520*** | 4.617** | 12.119*** | LR-spatial error | 24.998*** |
| | | [0.001] | [0.000] | [0.032] | [0.000] | | [0.000] |
| | Log-likelihood | −277.348 | −72.211 | −234.608 | −11.571 | | |
| $W_2$ | LM-spatial lag | 142.366*** | 92.955*** | 85.460*** | 31.253*** | Wald-spatial lag | 58.850*** |
| | | [0.000] | [0.000] | [0.000] | [0.000] | | [0.000] |
| | Robust LM-spatial lag | 32.064*** | 46.326*** | 4.966** | 15.289*** | LR-spatial lag | 52.995*** |
| | | [0.000] | [0.000] | [0.026] | [0.000] | | [0.000] |
| | LM-spatial error | 146.583*** | 55.214*** | 128.449*** | 17.738*** | Wald-spatial error | 52.477*** |
| | | [0.000] | [0.000] | [0.000] | [0.000] | | [0.000] |
| | Robust LM-spatial error | 36.281*** | 8.585*** | 47.955*** | 1.774*** | LR-spatial error | 60.213*** |
| | | [0.000] | [0.003] | [0.000] | [0.183] | | [0.000] |
| | Log-likelihood | −277.348 | −72.211 | −234.608 | −11.571 | | |
| $W_3$ | LM-spatial lag | 199.698*** | 127.459*** | 80.025*** | 25.291*** | Wald-spatial lag | 49.611*** |
| | | [0.000] | [0.000] | [0.000] | [0.000] | | [0.000] |
| | Robust LM-spatial lag | 68.324*** | 64.120*** | 11.660*** | 19.367*** | LR-spatial lag | 50.772*** |
| | | [0.000] | [0.000] | [0.001] | [0.000] | | [0.000] |
| | LM-spatial error | 168.288*** | 91.106*** | 82.076*** | 6.388** | Wald-spatial error | 60.612*** |
| | | [0.000] | [0.000] | [0.000] | [0.011] | | [0.000] |
| | Robust LM-spatial error | 36.914*** | 27.768*** | 13.711*** | 0.463 | LR-spatial error | 64.566*** |
| | | [0.000] | [0.000] | [0.000] | [0.496] | | [0.000] |
| | Log-likelihood | −277.348 | −72.211 | −234.608 | −11.571 | | |

The values in the square brackets are $P$ values, ***, **, and * respectively represent significance at 1%, 5%, and 10% levels

Our results were consistent with Tian and Feng (2021), Duan and Xia (2022), (Song et al. 2020), Fan et al. (2021), and Li and Du (2021), which respectively studied the impact of environmental regulation on green scale economy, green product innovation, environmental innovation and green innovation efficiency, and confirmed Porter's hypothesis. However, other studies have drawn different conclusions. Based on the data of Xi'an City (China) from 2003 to 2016, Zhang et al. (2020) showed that there was an inverted U-shaped relationship between environmental regulation and green innovation efficiency. By studying 27 OECD countries, Wang et al. (2019) believed that within a certain degree of strictness, environmental policies had a positive impact on green productivity growth, and when environmental regulation policies were strictness to a certain degree, the compliance cost was greater than the innovation offset effect.

The indirect environmental regulation effects and its quadratic were both significantly positive, indicating that there was always a positive spatial spillover effect in the surrounding regions. The possible reasons are as follows: First, the increase in the intensity of local environmental regulation encourages industries to flow to surrounding areas, which increases the income level of undertaking areas and the investment in green innovation R&D, thus improving the level of green innovation (Hille et al. 2019; Omri and Kahouli 2014). Second, the increase in the intensity of environmental regulations increases the cost of environmental protection, prompting enterprises to reduce production, close down high-pollution businesses, or reduce wages (Berman and Bui 2001; Liu et al. 2017; Sheng et al. 2019). Therefore, the released and lost human capital flows to the surrounding areas, which is conducive to the green innovation. Third, because the adjacent areas were likely to have similar development levels and geographical locations, the environmental regulations had strong reference significance. Therefore, the local environmental policies influenced the neighborhood

**Table 6** Estimates from the three models from 2006 to 2020

| Variable | Non-spatial FE model | W$_1$ | | W$_2$ | | W$_3$ | |
|---|---|---|---|---|---|---|---|
| | | Static SDM | Dynamic SDM | Static SDM | Dynamic SDM | Static SDM | Dynamic SDM |
| $W \cdot GI_t$ | | 0.306* | 0.658*** | 0.310*** | 0.604*** | 0.441*** | 0.783*** |
| | | (1.918) | (11.475) | (5.463) | (9.869) | (5.571) | (19.106) |
| $GI_{t-1}$ | | | 1.067*** | | 1.033*** | | 1.079*** |
| | | | (31.097) | | (33.163) | | (34.457) |
| $W \cdot GI_{t-1}$ | | | −1.036*** | | −0.631*** | | −0.897*** |
| | | | (−11.103) | | (−9.309) | | (−12.104) |
| ER | −0.191** | −0.113 | −0.109** | −0.203** | −0.121*** | −0.177* | −0.127*** |
| | (−2.082) | (−1.077) | (−2.218) | (−2.313) | (−2.965) | (−1.950) | (−3.064) |
| MD | −0.208*** | −0.184*** | 0.063 | −0.221*** | 0.106 | −0.200*** | 0.102 |
| | (−3.308) | (−2.888) | (0.600) | (−3.557) | (1.577) | (−3.208) | (1.440) |
| ER$^2$ | 0.232** | 0.129 | 0.116** | 0.237*** | 0.134*** | 0.206** | 0.143*** |
| | (2.473) | (1.203) | (2.340) | (2.638) | (3.330) | (2.205) | (3.483) |
| $W \cdot ER$ | | 0.280 | −0.114 | −0.022 | 0.317*** | −0.083 | 0.076 |
| | | (0.367) | (−0.067) | (−0.093) | (4.249) | (−0.183) | (1.265) |
| $W \cdot MD$ | | −0.161 | −0.363** | 0.248*** | −0.138 | 0.349** | −0.295 |
| | | (−0.424) | (−2.026) | (2.776) | (−1.222) | (2.063) | (−1.622) |
| Control variables | Control | Control | Control | Control | Control | Control | Control |
| R$^2$ | 0.736 | 0.943 | 0.984 | 0.949 | 0.988 | 0.948 | 0.987 |
| Log-likelihood | −11.571 | 5.282 | 267.747 | 27.259 | 305.138 | 24.156 | 299.593 |

The values in brackets are $T$ values, ***, **, and * respectively represent significance at the 1%, 5%, and 10% levels

**Table 7** Effect decomposition of the dynamic SDM

| Variable | W$_1$ | | | W$_2$ | | | W$_3$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | Direct effect | Indirect effect | Total effect | Direct effect | Indirect effect | Total effect | Direct effect | Indirect effect | Total effect |
| ER | −0.104** | 0.126** | 0.022 | −0.107*** | 0.140*** | 0.033 | −0.121*** | 0.203*** | 0.083 |
| | (−2.145) | (1.971) | (0.522) | (−2.629) | (2.770) | (0.964) | (−2.801) | (2.608) | (1.192) |
| MD | 0.067* | 0.152 | 0.218* | 0.120*** | 0.143* | 0.262** | 0.115*** | 0.354* | 0.469** |
| | (1.715) | (1.485) | (1.643) | (2.753) | (1.673) | (2.156) | (2.822) | (1.860) | (2.097) |
| ER$^2$ | 0.123** | 0.297* | 0.421* | 0.160*** | 0.291** | 0.451** | 0.176*** | 0.821** | 0.998** |
| | (2.242) | (1.684) | (1.937) | (2.917) | (2.015) | (2.390) | (3.252) | (2.371) | (2.576) |
| GS | 0.082*** | 0.096 | 0.178** | 0.066*** | 0.080 | 0.147** | 0.062** | 0.095 | 0.157** |
| | (3.301) | (1.276) | (2.129) | (2.659) | (1.428) | (2.392) | (2.442) | (1.531) | (2.312) |
| TO | 0.199*** | −0.096 | 0.103 | 0.104** | −0.062 | 0.042 | 0.134*** | −0.078 | 0.056 |
| | (4.525) | (−1.278) | (1.068) | (2.358) | (−1.132) | (0.563) | (2.800) | (−1.352) | (0.694) |
| IC | 0.040 | 0.343** | 0.382* | 0.069 | 0.611*** | 0.680*** | 0.061 | 0.137** | 0.197** |
| | (0.888) | (2.333) | (1.912) | (1.577) | (5.402) | (5.155) | (1.351) | (2.532) | (2.507) |
| IPR | −0.145*** | −0.177 | −0.322 | −0.079* | −0.054 | −0.132 | −0.170*** | −0.110 | −0.280 |
| | (−3.481) | (−0.454) | (−0.801) | (−1.887) | (−0.432) | (−0.980) | (−3.924) | (−0.290) | (−0.715) |

The values in brackets are $T$ values, ***, **, and * respectively represent significance at 1%, 5%, and 10%

environmental regulations through the "demonstration-imitation" mechanism, that is, as they had "race to the top" characteristics, they had a positive spatial interaction effect on the neighborhood green innovation developments.

There are some differences between our results and existing studies. Guo et al. (2019) found that environmental regulations have no significant impact on green innovation in surrounding areas, which believed that the development of local environmental regulations would increase the financing difficulty of polluting enterprises, thus stimulating some enterprises to migrate to surrounding areas, which may not promote green technology innovation in surrounding areas.

Peng (2020) and Cai and Ye (2022) found that environmental regulations inhibited green innovation in surrounding areas, which argued that environmental regulations in surrounding areas exacerbate local pollution emissions and produce pollution refuge effect. However, Dong et al. (2020) and Li and Du (2021) believed that the neighborhood effect of environmental regulation on green innovation was a U-shaped impact. The reason for the divergence of results may be that, in terms of explained variables, green innovation (green patent data) was intensively discussed in this paper, while Peng (2020) focused on green productivity and Li and Du (2021) paid attention to green innovation efficiency. In addition, Cai and Ye (2022) conducted an empirical analysis based on data of city-level units in China from 2008 to 2015, Guo et al. (2019) and Dong et al. (2020) based on data of provincial units from 2007 to 2016. However, this paper examined the impact of environmental regulation and market demand on green innovation simultaneously, which made an empirical analysis based on the data of provincial units from 2006 to 2020 due to the limitation of the availability of market demand data. To sum up, different research results may be caused by different explained variables, research periods, and research objects.

(2) Market demand

The direct effects of green market demand were significantly positive under three spatial weight matrixes, indicating that market demand could promote local green innovation improvements, and confirmed $H_3$. The green technology supply and demand mechanism is the fundamental driving force behind green innovation. As some green products can bring added value to customers, they are willing to pay a premium for them (Horbach et al. 2013; Kammerer 2009). With the improvement in green consumption awareness and consumption levels (Cai and Li 2018), green market demand increases. Therefore, enterprises that pay attention to market conditions are more willing to implement green innovation activities to increase their competitive advantage and obtain greater benefits (Demirel and Kesidou 2019), which improves the overall regional green innovation level.

The research results were similar to most existing studies, differently, the existing studies mostly focused on empirical results at the enterprise level in European countries (Cainelli et al. 2020; Horbach et al. 2012; Kiefer et al. 2019; Triguero et al. 2013). Cai and Li (2018) confirmed the promoting effect of consumers' green demand on ecological innovation from the Chinese firm level, and our study further found evidence that market demand promoted green innovation at the regional level of China. However, the results were at odds with del Río et al. (2017) and Jové-Llopis and Segarra-Blasco (2018). Based on the data of Spanish enterprise-level innovation from 2009 and 2008 to 2014 respectively, their research showed that market factors were not the main driving factor of ecological innovation, which might be because Spanish consumers' environmental awareness was relatively weak at that time and their willingness to pay for ecological products was relatively low.

The indirect effects of market demand were significantly positive, indicating that the local green technology market demand had significant positive spillover effects on the neighboring regions. As changes in market demand depend mainly on consumers, with the continuous development of transportation and communication, inter-regional population mobility and communication are being constantly enhanced (Tang et al. 2020), which means that areas with high green market demand can subtly influence the level and awareness of green consumption in the surrounding areas, which in turn improves their green innovation levels through this "ripple effect" (Dong et al. 2020; Zhu and Lee 2021).

(3) Control variables

The direct effects of government support under three spatial weight matrixes were significantly positive; however, the indirect effects were not significant, which indicated that government support for scientific and technological innovation can promote and enhance the subjective initiatives of local green innovation, which would improve the local innovation level (Chen et al. 2019; Zeng et al. 2021; Zhao and Li 2021; Zhou et al. 2021). Government support reflects the government's attitude towards innovation, reduces the uncertainty of enterprise innovation, and enhances innovation confidence, and government investment can also reduce the financial pressures on enterprises and encourage innovative enterprises to implement innovative activities.

The direct effects of trade openness were significantly positive, which indicated that the foreign investment brought by open trade can promote local green technology innovation and development. Open trade can enable foreign enterprises to increase their investment, which gives Chinese enterprises sufficient funds for green product research and development. Therefore, trade opening could directly encourage green enterprises to conduct green innovation activities in China.

The direct effects of the infrastructure construction level were not significant, but the indirect effect was significantly positive, indicating that the local infrastructure construction improvements had a significant positive spatial correlation effect on the surrounding areas. Transportation, communication, and other infrastructure construction can reduce the costs of inter-regional talent exchanges and increase efficiency. Therefore, the infrastructure construction improvements in lagging areas could allow for the building of communication bridges with surrounding areas, fill the vacancies in the regional communication network, and

**Table 8** Robustness test results

| Variables | Use investment in industrial pollution treatment to measure *ER* | | | Use sewage charge to measure *ER* | | |
|---|---|---|---|---|---|---|
| | Direct effect | Indirect effect | Total effect | Direct effect | Indirect effect | Total effect |
| *ER* | −0.044* | 0.041** | −0.003 | −0.193*** | 0.073** | −0.121*** |
| | (−1.871) | (2.220) | (−0.170) | (−3.593) | (2.081) | (−3.197) |
| *MD* | 0.142*** | 0.139*** | 0.281*** | 0.119*** | 0.121*** | 0.239*** |
| | (3.284) | (2.785) | (3.595) | (2.825) | (2.823) | (3.371) |
| $ER^2$ | 0.058*** | 0.320*** | 0.378*** | 0.120*** | 0.227*** | 0.346*** |
| | (2.906) | (4.227) | (4.462) | (3.132) | (2.915) | (3.556) |
| Control variables | Control | Control | Control | Control | Control | Control |

The values in brackets are t values, ***, **, and * respectively represent significance at 1%, 5%, and 10% levels

significantly promote green innovation improvements in the neighborhood.

The direct effects of intellectual property protection were significantly positive, but the indirect effects were not significant, which indicated that intellectual property protection improvements could inhibit local green innovation development. As enterprises need to invest a great deal of manpower, materials, and financial resources in green innovation, knowledge has a diffusion and spillover effect, which means that intellectual property protection is very important. However, only when this protection reaches a certain level would enterprises choose self-green innovation; otherwise, they would be more inclined to imitate pioneering green technology enterprises. Since most of China's green innovation is still in the imitative innovation stage, the enhancement of intellectual property protection will increase in the cost of implementing green innovation, thus having a significant negative impact on local green innovation.

## Robustness test

In basic regression, environmental regulation was measured by constructing comprehensive index of discharge/utilization of three types of pollutants by entropy method. As environmental regulation has a variety of measurement methods, the robustness test was conducted by changing the environmental regulation measurement methods. On the one hand, industrial pollution control investment per unit output value was used to measure the intensity of investment-type environmental regulation. On the other hand, the amount of sewage charge was used to measure the implementation cost-based environmental regulation. The estimation results for the dynamic SDM model under economic distance weight matrix after replacing the environmental regulation measurements are shown in Table 8.

The results showed that the estimation results for the direct effects of environmental regulation were all significantly negative, the quadratic terms and the indirect effects were all significantly positive, and the direct and indirect market demand effects were significantly positive. Their direction and significance were the same as the basic regression results, so the results were considered robust.

## Endogeneity problem

However, the dynamic SDM cannot solve the simultaneous endogeneity problem caused by the interaction between the explanatory variables and the explained variables. While environmental regulation and market demand affect regional green innovation, green innovation in turn influences the formulation of environmental policy and the changes in market demand. As green innovation improves, environmental policies are accordingly adjusted to raise the environmental regulation thresholds. Furthermore, the presence of more green products and services inevitably increases market demand, which leads to greater green innovation production to balance supply and demand. Therefore, following (Halleck Vega and Elhorst 2017), the first-order lag term for the environmental regulation and market demand endogenous explanatory variables and the explained green innovation variable were first selected as the instrumental variables. Second, to further control the environmental regulation endogeneity, the ventilation coefficient (*VC*) was taken as the environmental regulation instrumental variable for the time lag terms (Hering and Poncet 2014).

The ventilation coefficient, which is equal to the product of wind speed and boundary layer height (Jacobson 2002), was chosen as the instrumental environmental regulation variable because, first of all, when considering the same amount of air pollutants, regions with low ventilation coefficients have more stringent environmental regulations. As the ventilation coefficient only depends on natural phenomena such as the climate conditions, it only affects the regional green innovation by influencing the environmental policies. The data were derived from the ERA-Interim database of the European Center for Medium-Range Weather Forecasts

**Table 9** System GMM estimation results based on SDM

| Variables | $W_1$ | | $W_2$ | | $W_3$ | |
|---|---|---|---|---|---|---|
| | Time lag term as IV | Time lag term and exogenous variable as IV | Time lag term as IV | Time lag term and exogenous variable as IV | Time lag term as IV | Time lag term and exogenous variable as IV |
| $GI_{t-1}$ | 0.826*** | 0.847*** | 0.921*** | 0.917*** | 0.903*** | 0.897*** |
| | (32.230) | (35.280) | (38.890) | (40.750) | (37.320) | (38.960) |
| ER | −0.148*** | −0.139** | −0.177*** | −0.185*** | −0.196*** | −0.201*** |
| | (−2.590) | (−2.520) | (−3.190) | (−3.500) | (−3.420) | (−3.690) |
| MD | 0.062* | 0.096** | 0.055* | 0.056* | 0.048* | 0.070* |
| | (1.720) | (2.520) | (1.690) | (1.700) | (1.640) | (1.780) |
| $ER^2$ | 0.210*** | 0.194*** | 0.220*** | 0.220*** | 0.249*** | 0.244*** |
| | (3.570) | (3.420) | (3.910) | (4.110) | (4.270) | (4.400) |
| $W \cdot ER$ | 0.328** | 0.252* | 0.480*** | 0.505*** | 0.263** | 0.291** |
| | (2.000) | (1.650) | (5.050) | (5.410) | (2.190) | (2.500) |
| $W \cdot MD$ | 0.271* | 0.280** | 0.146* | 0.212*** | 0.236* | 0.353*** |
| | (1.880) | (2.070) | (1.830) | (2.740) | (1.960) | (3.040) |
| Control variables | Control | Control | Control | Control | Control | Control |
| Sargan test | 398.001 | 407.757 | 352.831 | 366.086 | 368.36 | 378.074 |
| | [0.230] | [0.150] | [0.240] | [0.170] | [0.210] | [0.130] |
| AR(1) test | 15.832 | 13.994 | 14.263 | 12.942 | 8.731 | 8.59 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| AR(2) test | 4.614 | 5.236 | 4.213 | 5.134 | 3.437 | 4.647 |
| | [0.644] | [0.629] | [0.759] | [0.680] | [0.463] | [0.498] |
| Wald test | 10,900.62 | 10,583.48 | 10,372.88 | 10,128.47 | 10,475.37 | 10,349.78 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |

The values in brackets are *T* values, and the values in square brackets are the adjoint probability of the statistic. ***, **, and * respectively represent significance 1%, 5%, and 10% at levels

(ECMWF). As only raster data was obtained, it was still necessary to match this with the longitude and latitude of the capital cities to obtain the regional annual ventilation coefficients. The system GMM estimation for the SDM was conducted under three spatial weight matrixes, and the results for which are shown in Table 9.

The results showed that the adjoint probabilities for the Sargan test statistics were all greater than 0.1, indicating that there was no over recognition. The adjoint probabilities of the AR (1) test statistics were all less than 0.1, and those for the AR (2) test statistics were all more than 0.1, indicating that there was no second-order autocorrelation and the instrumental variable was valid. Regardless of using the first-order lag term or using both the first-order lag term and the air circulation coefficient as instrumental variables, the environmental regulation parameter estimation results were significantly negative, and the second-order term and spatial term were significantly positive. The parameter estimation results for the market factor were significantly positive. These results showed that the environmental regulation effect on regional green innovation had a U-shaped relationship, there was a positive spatial spillover effect, and the

market demand promoted green innovation. As the system GMM estimation results for the dynamic SDM were similar to the basic regression results, and the regression results were proven robust.

## Mechanism test

The theoretical analysis showed that the environmental policies and market demand may not play direct roles in green innovation, but affected the regional green innovation by changing the innovation input. When the environmental regulation intensity is weak, because of the "cost compliance" effect, the cost increases lead to a decrease in the innovation input, which is not conducive to green innovation development. As the environmental policy intensity increases, the innovation investment increases because of the "innovation compensation" effect, which improves the green innovation. However, an increase in green market demand can reduce green innovation uncertainty, significantly increase the expected profit, and enhance enterprise green innovation motivation, and an increase in innovation input can improve

**Table 10** Mediating effect test for *RD*

| Variable | Dependent variable: mediating variable (with $ER^2$) | | | Dependent variable: mediating variable (without $ER^2$) | | | Add mediating variable in basic regression model | | |
|---|---|---|---|---|---|---|---|---|---|
| | Direct effect | Indirect effect | Total effect | Direct effect | Indirect effect | Total effect | Direct effect | Indirect effect | Total effect |
| *ER* | −0.048 | 0.008 | −0.040* | −0.066* | 0.060* | −0.006 | −0.098*** | 0.122*** | 0.024 |
| | (−1.019) | (0.166) | (−1.941) | (−1.792) | (1.943) | (0.880) | (−2.649) | (2.843) | (0.947) |
| *MD* | 0.079* | 0.094** | 0.173** | 0.079* | 0.033 | 0.111 | 0.087*** | 0.167*** | 0.254*** |
| | (1.872) | (2.346) | (2.444) | (1.943) | (0.637) | (1.549) | (3.405) | (2.709) | (3.115) |
| $ER^2$ | 0.021 | 0.015 | 0.035 | | | | 0.149*** | 0.154 | 0.303** |
| | (0.399) | (0.256) | (0.376) | | | | (2.836) | (1.570) | (2.103) |
| *RD* | | | | | | | 0.114** | 0.278** | 0.392** |
| | | | | | | | (2.372) | (2.036) | (2.247) |
| Control variables | Control | Control | Control | Control | Control | Control | Control | Control | Control |

The values in brackets are *T* values, \*\*\*, \*\*, and \* respectively represent significance at the 1%, 5%, and 10% levels

the green innovation level. The regression results under the economic distance weight matrix are shown in Table 10.

As shown in Table 10, when the dependent variable was innovation input, the total environmental regulation effect was significantly negative after adding the environmental regulation quadratic term. While all the quadratic term effects were not significant, there was no "U" shaped effect for the impact of environmental regulation on innovation input. When the environmental regulation quadratic term was removed, the results showed that the direct effect of environmental regulation was significantly negative, and the indirect effect was significantly positive, which implied that environmental regulation increases environmental costs and squeezes out local innovation input. The conclusion was consistent with Yuan and Xiang (2018), who believed that environmental regulation had a crowding out effect on R&D investment, and innovation initiatives were usually hindered by compliance costs of environmental regulation. However, some studies suggested that environmental regulation can promote R&D spending. Using a quasi-natural experiment, Chakraborty and Chatterjee (2017) found that environmental regulations significantly promoted innovation expenditures of dye manufacturers in India. Costa-Campi et al. (2017) showed that the rigor of regulations, R&D subsidies and environmental taxes had a positive impact on the level of environmental R&D investment. At the same time, due to the "pollution heaven" effect (Copeland and Taylor 2004), the surrounding areas that have weak environmental regulations attract more investment, and the innovation input increases accordingly. The direct effect of market demand was significantly positive, indicating that under the market mechanism,

an increase in market demand provides the impetus for green innovation and accordingly results in an increase in innovation input (Barge-Gil and López 2014; Garcia-Quevedo et al. 2017).

When the innovation input was added to the basic regression model, the direct effect of innovation input was significantly positive, indicating that an increase in innovation input can significantly improve regional green innovation levels (Li et al. 2019). The significance and direction of the estimated direct and indirect effects of environmental regulation and market demand were similar to the basic regression results. Specifically, each additional environmental regulation unit reduces green innovation by 9.8%, while in the basic regression model, each environmental regulation change resulted in a green innovation change of 10.7%. When focused on the innovation input, the environmental regulation impact on green innovation was slightly reduced, which indicated that environmental regulation partly affects regional green innovation by influencing innovation input. However, when the market demand increased by one unit, the green innovation increased by 8.7%, while in the basic regression model, the per unit change in market demand resulted in a 12.0% green innovation change. When focused on the innovation input, the market demand impact on green innovation was significantly reduced, which indicated that market demand partly affects regional green innovation through innovation input, and the proportion of such an effect is significantly higher than that of environmental regulation. Environmental regulation inhibits regional innovation input through the "cost compliance" effect, which is also unfavorable to regional green innovation, but market demand plays an incentive role in innovation input, thus promoting the improvement of the green innovation level.

**Table 11** Estimation results for the dynamic SDM by region

| Variable | Eastern region | | | Central region | | | Western region | | |
|---|---|---|---|---|---|---|---|---|---|
| | Direct effect | Indirect effect | Total effect | Direct effect | Indirect effect | Total effect | Direct effect | Indirect effect | Total effect |
| $ER$ | − 0.067 | 0.141 | 0.074* | 0.142 | − 0.296*** | − 0.154 | 0.099 | − 0.141 | − 0.042 |
| | (− 0.773) | (1.340) | (1.722) | (1.487) | (− 2.688) | (− 1.576) | (0.530) | (− 0.727) | (− 0.790) |
| $MD$ | 0.073* | 0.168* | 0.241** | 0.052 | 0.154* | 0.206* | − 0.001 | 0.021 | 0.020 |
| | (1.661) | (1.831) | (2.014) | (1.200) | (1.861) | (1.870) | (− 0.020) | (0.467) | (0.261) |
| $ER^2$ | 0.103 | 0.038 | 0.141 | − 0.112 | − 0.149 | − 0.261 | − 0.138 | − 0.141 | − 0.280 |
| | (1.182) | (0.331) | (0.790) | (− 1.176) | (− 0.987) | (− 1.532) | (− 0.706) | (− 1.618) | (− 1.140) |
| $GS$ | 0.087** | 0.132 | 0.219* | 0.116** | 0.294* | 0.410** | 0.026 | − 0.243 | − 0.217 |
| | (2.156) | (1.393) | (1.903) | (2.291) | (1.712) | (2.004) | (0.737) | (− 1.489) | (− 1.269) |
| $TO$ | 0.014 | 0.534*** | 0.548** | 0.074 | 0.084 | 0.157 | − 0.097** | − 0.019 | − 0.116 |
| | (0.214) | (2.641) | (2.509) | (1.444) | (0.862) | (1.192) | (− 2.120) | (− 0.301) | (− 1.340) |
| $IC$ | 0.101 | 0.790* | 0.891* | 0.173* | 0.345 | 0.518 | − 0.206 | 0.338 | 0.133 |
| | (1.537) | (1.841) | (1.924) | (1.741) | (1.008) | (1.319) | (− 1.460) | (0.452) | (0.164) |
| $IPR$ | 0.381*** | 0.187 | 0.569 | 0.035 | 0.125 | 0.159 | − 0.002 | − 0.121 | − 0.123 |
| | (2.873) | (0.651) | (1.505) | (0.644) | (1.109) | (1.169) | (− 0.041) | (− 0.558) | (− 0.526) |

The values in brackets are $T$ values, ***, **, and * respectively represent significance at the 1%, 5%, and 10% levels

# Further study

## Study by region

The spatial and temporal evolutionary analysis of green innovation showed that there were significant differences in the regional green innovation, with a "step-down" characteristic in the eastern, central, and western regions.[1] Therefore, it was necessary to examine whether there was regional heterogeneity in the green innovation driving factors (Wu et al. 2021a). The estimation results of the dynamic SDM under economic distance weight matrix are shown in Table 11.

As shown in Table 11, the estimated results for environmental regulation and market demand showed obvious spatial heterogeneity. First, while the environmental regulation direct and indirect effects were not significant in the eastern region, the total effect was positively significant, and while the direct effect was not significant in the central region, the indirect effect was negatively significant; however, no effects were significant in the western region. Because of the rapid economic development in eastern China, there was an early implementation of environmental policies, and many enterprises have attained the established policy standards (Chen et al. 2017). Therefore, as the environmental regulations no longer motivate them to conduct further green

innovation, they only play a small role in China's overall green innovation. Different from the full sample estimation results, the environmental regulation in the central region had significant negative green innovation spillover effects in the neighborhood, which indicated that the environmental regulation "demonstration-imitation" mechanism was no longer applicable, leading to a "pollution heaven" situation (Cai and Ye 2022; Peng 2020). The "pollution paradise" hypothesis was proposed by Copeland and Taylor (2004) which held that strict environmental policies led to increased environmental spending, which could accelerate the transfer of the polluting enterprises to nearby areas that had less environmental regulations and the forming of a "pollution heaven." The research results were similar to Li and Wu (2017), who believed that environmental regulations in areas with low political attributes had significant negative spatial spillover effects. Because the central region is experiencing rapid development, the local governments are lowering environmental standards to achieve "nesting to attract phoenix" and promote their economic development, that is, there is a competitive "race to the bottom." This "high pollution" development mode has therefore significantly reduced the green innovation level. However, in western China, on the one hand, due to the low degree of environmental regulation, it is difficult to impose a green innovation supervisory role on the enterprises, and the environmental cost is relatively low compared with the cost of implementing green innovation (Chen et al. 2017). Therefore, as rational people, enterprises choose to continue to use "dirty technology" and lack the motivation for green innovation. On the other hand, as the saying goes, "even a clever housewife cannot cook a meal without rice." Due to remote geographical location,

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[1] ①Eastern region: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan; Central region: Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan; Western region: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.

backward economic development, and lack of green innovation resources such as capital and talents, it is difficult for environmental regulations to promote green innovation development.

The direct, indirect, and total effects of market demand were significantly positive in the eastern region, and the indirect and total effects were significantly positive in the central region, but again, no effects were significant in the western region, which was similar to the research results in Chen et al. (2017), who believed that while the market demand in the eastern, central, and western Chinese regions had a significant positive impact on ecological innovation, there was a smaller impact in the western region. These results showed that the higher green market demand in the eastern region promoted the overall green innovation activities in the region, the green technology market demand in the central region had a radiation effect that promoted the green innovation levels in the surrounding areas, but due to western China's remote geographical location and backward opening-up policies, it has been difficult to garner the needed material and human resources. Furthermore, as the western region's average income and education levels are relatively low, the demand for a favorable ecological environment, energy conservation, and environmental protection products is relatively low, which means that increasing the green market demand and promoting green innovation development is difficult.

The direct effect and total effect of government support were significantly positive in the eastern region, all effects were significantly positive in the central region, and none in the western region. The possible reason lied in the low government support for innovation and the lack of innovation resources in western China, and it has been difficult to stimulate green innovation vitality in the enterprises. The correlation coefficient of government support in central region was significantly higher than that in eastern region, indicating that government innovation input in central region could better promote the improvement of green innovation level. The indirect and total effects of trade opening were significantly positive in the eastern region, and the direct effect was significantly negative in the western region, while none were significant in the central region. This indicates that the opening up of the eastern developed region was able to attract foreign-funded enterprises to implement green innovation activities in a large area around the region, which led to a loss of capital, talent, and other resources in the less developed western region, which was not conducive to green innovation improvements. The indirect and total effects of infrastructure construction were significantly positive in the eastern region, and the direct effect was significantly positive in the central region, but all effects are not significant in the western region, which indicated that the improvement of infrastructure construction level in eastern China could

enhance the communication capacities in the surrounding areas and provide the impetus to promote green innovation, and the enhancement of communication capacity in central China could help it better absorb knowledge and improve the level of green innovation. The intellectual property protection direct effect in the eastern region was significantly positive, while all the effects were not significant in the central and western regions, which was different from the regression results of the full sample. It indicated that the intellectual property protection and green innovation in eastern China have reached a certain level, and the higher intellectual property protection levels in eastern China have been able to improve the expected local green innovation output income, enhance enterprise green innovation confidence, and thus promote green innovation implementation.

## Study by time

The spatial and temporal green innovation evolution analysis showed that the overall level and spatial–temporal distribution of regional green innovation keep changing from 2006 to 2020. Therefore, the effect of environmental regulation and market demand on green innovation may also change over time. Based on the above reasons, the study period was divided into two stages, 2006–2013 and 2013–2020, for the further analysis, the results of which are shown in Table 12.

As can be seen from Table 12, the estimated environmental regulation and market demand results revealed significant temporal heterogeneity. From 2006 to 2013, the direct effect of environmental regulation was significantly positive, the indirect effect and the direct effect of the quadratic term were significantly negative, which indicated that there was an inverted U-shaped relationship between environmental regulation and green innovation, and environmental regulation had "pollution paradise" effect. At this time, China had proposed a series of guiding policies to accelerate the economic growth mode transformation to energy conservation, environmental protection, and independent innovation capacity (Li et al. 2019). The just proposed environmental regulation policies made enterprises overwhelm and could only meet the policy requirements by increasing environmental protection expenditure. The increased environmental protection cost squeezed out innovation input and stifled any regional green innovation improvement. From 2013 to 2020, the direct environmental regulation effect was significantly negative, the indirect effect was significantly positive, the direct quadratic term effect was significantly positive, and the indirect effect was significantly negative, which indicated that the environmental regulation had both a positive "U" shaped effect on local green innovation and an inverted "U" shaped effect on the green innovation in surrounding areas.

From 2006 to 2013, the direct effect of market demand was not significant, while the indirect effect was significantly

**Table 12** Estimation results for the dynamic SDM by time

| Variable | 2006–2013 | | | 2013–2020 | | |
|---|---|---|---|---|---|---|
| | Direct effect | Indirect effect | Total effect | Direct effect | Indirect effect | Total effect |
| ER | 0.778*** | −0.351** | 0.428*** | −0.116* | 0.103** | −0.013 |
| | (4.056) | (−2.328) | (2.976) | (−1.707) | (2.011) | (−0.402) |
| MD | 0.080 | −0.174** | −0.094 | 0.003 | 0.116** | 0.118 |
| | (1.171) | (−2.015) | (−0.803) | (0.016) | (2.078) | (0.850) |
| $ER^2$ | −0.382*** | 0.029 | −0.353* | 0.102* | −0.167** | −0.065 |
| | (−3.470) | (0.221) | (−1.900) | (2.092) | (−2.337) | (−0.787) |
| GS | −0.067 | −0.277* | −0.344** | 0.123*** | 0.045 | 0.168** |
| | (−1.132) | (−1.903) | (−2.441) | (3.299) | (0.701) | (2.369) |
| TO | 0.051 | −0.859*** | −0.808*** | −0.173** | 0.109 | −0.064 |
| | (0.535) | (−3.913) | (−3.332) | (−2.304) | (1.102) | (−0.615) |
| IC | 0.233** | 0.571** | 0.804** | 0.063 | −0.104 | −0.041 |
| | (2.575) | (2.381) | (2.158) | (1.163) | (−0.360) | (−0.141) |
| IPR | −0.802*** | 0.605 | −0.197 | 0.108 | −0.760 | −0.652 |
| | (−6.708) | (1.271) | (−0.391) | (1.039) | (−1.154) | (−1.014) |

The values in brackets are $T$ values, ***, **, and * respectively represent significance at the 1%, 5%, and 10% levels

negative. At the fifth Plenary Session of the 16th CPC Central Committee in 2005 and the 17th CPC National Congress in 2007, environmental protection issues began to be widely promoted, after which the green market demand gradually increased. The increasing local green market demand made the green innovation resources of surrounding areas gather to it, resulting in the "siphon" effect and led to the decline of the green innovation level of surrounding areas. From 2013 to 2020, the awareness of green consumption was further enhanced, and the improvement of transportation and communication facilities led to more frequent inter-regional communications. Therefore, the increase of local market demand promotes the green innovation development in surrounding areas.

From 2006 to 2013, the indirect effect of the government support control variable was significantly negative, and from 2013 to 2020, the direct effect was significantly positive. These results showed that from 2006 to 2013, areas with high government support gained a greater share of the innovation resources, which had a negative spillover effect on the surrounding areas. From 2013 to 2020, the government's innovation incentive policies realized an improvement in local regional green innovation. From 2006 to 2013, the indirect effect of trade opening was significantly negative, and the direct effect was significantly positive from 2013 to 2020. It indicated that from 2006 to 2013, the regional opening to the outside world attracted an inflow of foreign capital and the flow of resources and talents in surrounding areas, thus inhibiting the improvement of green innovation in surrounding areas. Due to increasing international attention on environmental and climate issues and stricter environmental policies in foreign countries, from 2013 to 2020 the opening

up to the outside world provided the space for foreign polluting enterprises to move their production activities to China, which was not conducive to the development of local green innovation. The direct effect and indirect effect of infrastructure construction from 2006 to 2013 were significantly positive, indicating that the level of infrastructure construction in China increased rapidly during this period, which promoted the knowledge flow between regions and further promoted the development of overall green innovation. From 2006 to 2013, the direct effect of intellectual property protection was significantly negative, indicating that green innovation in this period was still in its infancy, and most innovations were imitation. The improvement of intellectual property protection was not conducive to regional green innovation activities.

## Policy implications and limitations

This study employed a dynamic spatial Durbin model to empirically test Chinese provincial panel data and examined the impact of environmental regulations, market demand, and their spatial effects on regional green innovation. The main conclusions were as follows:

(1) Environmental regulation had a positive "U-shaped" effect on local green innovation and a positive spillover effect on neighborhoods, and market demand was found to have a significant positive effect on local green innovation and had a "ripple effect."

(2) The mechanism analysis showed that environmental regulation inhibited regional innovation input through

the "cost compliance" effect, which was unfavorable to regional green innovation; however, the "innovation compensation" effect of environmental regulation was not realized by changing the innovation inputs. Market demand had a stronger incentive effect on innovation input than environmental regulation, which promoted green innovation improvements.

(3) The environmental regulation and market demand effects on green innovation had obvious spatial and temporal heterogeneity. In eastern China, both environmental regulation and market demand promoted green innovation activities, the environmental regulation in the central region had a "race to bottom" mechanism, and the market demand had radiation effects, and environmental regulation and market demand had little effect on green innovation development in western China. From 2006 to 2013, there was an inverted U-shaped relationship between environmental regulation and local green innovation, and also a "pollution paradise" effect, and market demand showed a negative spillover effect on surrounding areas. From 2013 to 2020, environmental regulation had a positive "U" effect on local green innovation and an inverted "U" effect on the surrounding areas, and the increase of local market demand promoted green innovation in surrounding areas.

Based on these findings, the following policy recommendations are given. First, suitable environmental regulations need to be formulated. Local governments need to make comprehensive use of the various environmental regulation measures to maximize their effectiveness. At the same time, a "race to the top" mentality should be promoted to drive overall green innovation. Second, green consumption should be stimulated to enhance the market vitality of green products. The green consumption concept must be integrated into all aspects of people's lives, and then, green consumption encouraged by providing subsidies to customers who buy green products. Third, differentiated green innovation-driven policies should be implemented to achieve regional collaborative green innovation. The spatial spillover effect of green innovation should also be given full play to enhance the exchange of green innovation between the provinces and build a green innovation cooperation platform to realize effective regional collaborative green innovation.

However, the following limitations exist in this study. Considering the availability of market demand data, this study empirically analyzed the data at the provincial level in China. However, as discussed in the results, the effects of environmental regulation and market demand on green innovation in local and surrounding areas might be different due to the selection of data scales. Therefore, the next step of the study aims to address the data issue and conduct the analysis at the city level. In addition, the effects of different industries, as well as the impacts of environmental regulation and market demand on various types of green innovation, such as green product innovation and green process innovation, can be further considered to make more nuanced recommendations.

**Data availability** The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Declarations

**Ethics approval and consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Competing interests** The authors declare no competing interests.

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