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THE SPATIAL SPILLOVER EFFECTS OF GREEN BONDS: A LOCAL AND NEIGHBOURING PERSPECTIVE ON CARBON MITIGATION

Abstract: Green bonds have emerged as a crucial instrument in achieving dual carbon development goals. This study explores the carbon emission reduction effects and mechanisms of green bonds from an innovative local-neighbouring regional perspective, offering vital insights into realising comprehensive low-carbon transformation at the regional level. Utilising panel data from 30 Chinese provinces (including autonomous regions and municipalities directly under the central government) from 2007 to 2022, we investigate the mechanisms through which green bonds influence carbon emission intensity. Our findings demonstrate that green bonds significantly reduce carbon emission intensity, a conclusion that remains robust under Spatial Durbin Model testing. Upon decomposing the total effect, we reveal a nuanced impact: while green bonds effectively reduce local carbon dioxide intensity, disparities in environmental regulations and incentive policies across regions lead to the relocation of polluting enterprises to neighbouring areas. This study argues that while promoting the development of green bonds, it is imperative to strengthen inter-provincial communication and collaboration. Breaking down regional barriers and achieving coordinated development of green financial resources among regions is essential for reducing carbon emission intensity not only locally but also in neighbouring areas. These findings underscore the need for a holistic approach to green finance policy implementation to ensure widespread and equitable carbon reduction across China.

Keywords: green finance, green bonds, carbon emission intensity, spatial spillover effects

Introduction

Global industrialisation and urbanisation have driven economic development, but have concurrently caused significant environmental degradation. Notably, greenhouse gas emissions within the biosphere now far exceed the ecological carrying capacity. In response, the Central Committee of the Communist Party of China and the State Council have issued guiding documents outlining China's pathway to achieve its dual carbon goals (carbon peak and carbon neutrality) [1, 2].

Furthermore, against the backdrop of rapidly evolving global financial structures and the parallel advancement of enterprise digital transformation [3, 4], concepts such as sustainable finance and integrated energy systems featuring complementary power supply from renewable and conventional energy sources are gaining increasing prominence. This paradigm shift underscores the imperative to integrate Environmental, Social, and

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Governance (ESG) factors into the framework of a low-carbon economic model. These developments not only demonstrate China's firm resolve to transform its economic development model but also chart a clear direction for green finance to facilitate high-quality economic growth in China.

Green bonds, with their dual attributes of "green" and "finance", are a crucial component of China's green finance system and an indispensable force in achieving the "dual carbon" goals. As an important part of ecological civilisation construction, green bonds can alleviate issues such as the difficulty and high cost of financing for energy-saving and environmental protection enterprises, thereby meeting the diversified investment needs of investors. In December 2015, following the introduction of a series of green bond-related regulations by the People's Bank of China and the National Development and Reform Commission, the scale of China's green bond market rapidly expanded. In 2019, the total issuance of labelled green bonds in China ranked first globally. By the end of 2021, China had issued approximately 2.1 trillion yuan in labelled green bonds in domestic and international markets, making it the world's second-largest green bond market and a significant participant and leader in the global green bond market.

Existing literature mainly concentrates on the following aspects. Initially, some scholars have explored the influence of green finance development on regional carbon emissions from a macro level. In contrast, other studies have examined the impact of financial reform pilot zone policies on carbon productivity, indicating that the establishment of national financial reform pilot zones enhances urban carbon productivity through technology upgrade and industrial transformation driven by targeted financial supply release, with spillover effects on neighbouring cities.

Subsequently, at the micro level, most research has centred on the effect of green finance development on corporate investment and innovation. On one hand, green finance development restrains investment in energy-intensive and highly polluting firms, encouraging their diversified operations. The construction of green finance reform pilot zones cuts environmental firms' financing costs, expands financing scale, and boosts financing efficiency. On the other hand, green finance policies boost corporate green innovation motivation, raise green output, and increase green employment, thus promoting corporate green transformation.

Prior studies have predominantly examined the effects of green finance policies on regional carbon emissions, with a particular focus on green bonds. These studies have demonstrated that green finance policies can effectively drive carbon reduction, and green bonds have played a positive role in financing environmental projects. Some research has also shown that integrating green finance with the digital economy can strengthen its impact on energy consumption, particularly in densely populated areas. Furthermore, green finance has been found to reduce carbon emissions through both direct effects and spatial spillover effects, thereby lowering emissions in both local and neighbouring regions.

Despite these achievements, existing research still has several limitations:

1. Uncertain Implementation Effects of Green Bonds: In practice, the implementation of green bonds is susceptible to various external factors, and the actual carbon reduction effects may be uncertain.
2. Neglect of Spatial Factors: Most previous studies have not considered the impact of spatial factors on the relationship between green bonds and carbon emissions, lacking a systematic spatial analysis.

3. Insufficient Attention to Corporate Environmental Performance and Social Responsibility: Previous studies on provincial panel data mostly focused on the impacts of carbon emissions on corporate investment and innovation, with limited attention to corporate environmental performance and social responsibility.

To fill the above gaps, this paper proposes the following research questions:

1. How can spatial factors be integrated into the analysis framework of green bonds and carbon emission effects to more comprehensively and accurately evaluate the true impact of green bonds on carbon emissions?
2. How can the carbon - reduction effects of green bonds and their "local-neighbour" mechanisms be quantified?
3. How can green finance be utilised in the carbon emission trading market to facilitate the achievement of the "dual - carbon" goals? What mechanisms influence corporate carbon - reduction efforts?
4. Can green bonds play a coordinating role under varying intensities of environmental regulation to maximise corporate carbon - reduction effectiveness?

By constructing a spatial econometric model, this paper aims to provide empirical evidence for these questions and offer constructive suggestions for China’s carbon - reduction efforts from the perspective of green finance.

Literature review and research hypotheses

Green bonds and carbon emissions

With the rapid development of economic globalisation, international trade activities have become increasingly frequent. Consequently, issues such as global warming have intensified. There is now a broad consensus on the need to reduce carbon emissions and improve the human living environment. The Green Economy constituted one of the two central themes addressed at the United Nations Conference on Sustainable Development (UNCSD-2012), also widely referred to as Rio+20, held in Rio de Janeiro. In the period leading up to the conference, the United Nations Environment Programme (UNEP) played a leading role in advancing the discourse on the Green Economy. This effort culminated in the publication of its landmark report on the Green Economy, along with policy guidance covering the formulation of green economic policies, the measurement of progress, and the modeling of future impacts associated with a transition toward a Green Economy [5]. As a major emitter of carbon dioxide, China’s carbon peak and carbon neutrality goals, proposed in 2021, were first incorporated into the government work report. Subsequently, through various major political conferences, guidelines and strategies for energy conservation and emission reduction were gradually established. The "dual-carbon" goals not only represent a significant initiative taken by China as a responsible global power in environmental protection but also serve as a crucial focal point in the study of China’s carbon dioxide emissions. Therefore, the growing prominence of environmental issues has given rise to the green economy. Among the various factors influencing the development of the green economy, green barriers, which often take the form of implicit restrictions, have emerged as a significant constraint [6]. In this context, global concerns have arisen due to climate change and the depletion of resources, compelling governments and industries to implement measures to alleviate these enduring challenges [7]. The sustainable finance sector, exemplified by green bonds, and its developmental trends are currently attracting extensive attention. Moreover, research on sustainable finance practices, exemplified by green bonds, has found that the integration of environmental sustainability into the financial system is gaining increasing attention [8, 9].

In this context, the emerging model of the low-carbon economy has emerged, aiming to continuously improve the industrial credit system. By actively cultivating low-carbon industries on the basis of environmental protection and energy conservation, this model drives the green transformation and upgrading of enterprises [10, 11]. Moreover, further studies have indicated that different regions have differences in carbon trading settlement, accounting, taxation, risk control and other aspects [12]. Concurrently, the aforementioned findings have been corroborated by additional research. Scholars have delved into the specific mechanisms of green finance in the decarbonisation process. Their findings reveal that green finance significantly reduces carbon emissions both in the short and long terms. Importantly, the impact of green bonds on clean energy capacity is amplified in politically stable environments [13]. Based on these insights, the researchers propose that integrated green finance and growth policies can effectively promote renewable energy infrastructure development. They also stress the importance of maintaining political stability to attract investors and drive sustainable green energy growth [14].

Based on the above analysis, the following hypotheses are proposed:

H1: The development of green bonds significantly decreases carbon emission intensity.

The intensity of environmental regulation and carbon emissions

A number of scholars have centered their research on the role and impact of environmental regulations, thereby providing a solid theoretical foundation for this study [15-17].

Numerous studies have confirmed that green finance can enhance environmental outcomes and bolster sustainable development performance in both the short and long terms. Building on this, further research has shown that environmental regulation policies, when applied at the micro level, can drive carbon reduction. Furthermore, differentiated environmental regulation policies can not only enhance the efficiency level of green technological innovation but also exert varying effects on carbon emission reduction [18]. Subsequent studies by Li and Sun, focusing on the industry level, have revealed that different regulatory tools exert varying impacts on energy efficiency: environmental administrative penalties have a detrimental effect on China’s energy efficiency; market-incentivised environmental regulations yield a positive influence; whereas voluntary regulations demonstrate a negative, albeit statistically insignificant, correlation with energy efficiency [19]. Empirical analyses reveal that informal environmental regulation significantly suppresses pollution irrespective of regional economic development levels. Subsequent studies have quantified environmental policy performance among EU member states by evaluating their commitment to international environmental treaties and the stringency of the treaty portfolio they have ratified. This research provides a transparent ranking of member states’ environmental policy effectiveness and offers valuable recommendations for crafting robust environmental policies and regulations [20]. Given the uneven economic development across China’s regions, scholars have posited that informal environmental regulation might exhibit threshold and spatial spillover effects. Subsequent empirical analyses, leveraging panel threshold and spatial Durbin models, have demonstrated that the interplay of formal and informal regulations synergistically drives carbon reduction [21].

Based on the above analysis, the following hypotheses are proposed:

H2: Environmental regulation promotes the influence of green bonds on carbon emission intensity.

Green bond development and spatial spillover effect on carbon emission

Given the disparities in the intensity of environmental regulations and the policy incentive directions across various regions, cross-regional pollution and the relocation of polluting industries to adjacent areas remain possible, consequently reshaping the regional industrial landscape. Alternatively, when environmental regulations in a region tighten, although local enterprises may pursue in-situ technological innovation, the substantial burden imposed by environmental protection measures on high-polluting firms can escalate their investment costs and erode their market competitiveness. In such scenarios, polluting enterprises frequently choose to relocate to nearby regions with less stringent environmental regulations.

Further research has demonstrated that distinct types of environmental regulations exhibit significantly different spatial spillover effects. Moreover, the spatial impacts of informal environmental regulations cannot be overlooked. Currently, empirical evidence in this field remains limited, with only a few scholars having conducted exploratory studies. For example, Zhu and Li revealed that enhancing public participation in neighbouring regions contributes to improving environmental governance efficiency in those areas [22]. Wang et al. found that even in the absence of formal regulations or public attention in a local province, its level of public concern can still elevate wastewater treatment performance in adjacent provinces [23]. Additionally, Wu et al. employed game theory and the Spatial Durbin Model (SDM) to confirm the positive spatial effect of public participation on China’s overall "race-to-the-bottom" competition in environmental governance [24].

Therefore, we believe that variables related to economic and environmental issues generally have spatial dependencies, and ignoring these spatial dependencies may lead to biased model estimation results. Based on the above analysis, the following hypotheses are proposed:

H3: The development of green bonds has a significant spatial spillover effect on carbon emissions.

Research methodology

Variables

Dependent variable: The goal of carbon reduction is to pursue coordinated development of the environment and the economy. Compared to the single carbon dioxide emission indicator, both economic and environmental benefits are considered the best indicators for measuring carbon emission effects. GDP emphasises economic benefits, while carbon dioxide emissions relate to environmental conditions. Their ratio is carbon intensity (*CI*). The calculation of carbon dioxide emissions adopts the first method announced by IPCC (2006) [26], which calculates the carbon dioxide emissions related to fossil energy consumption ($CE_{direct.i,n}$) and industrial production processes ($CE_{direct-related.i,n}$).

The calculation formula for carbon emission intensity is presented in equation (1):

$$CI_{i,n} = \frac{CE_{direct.i,n} + CE_{direct-related.i,n}}{GDP_{i,n}} \tag{1}$$

where: $CE_{direct.i,n}$represents the carbon dioxide emissions from the final consumption of total raw coal, crude oil, and natural gas. For $CE_{direct-related.i,n}$, this study only considers cement production, which accounts for nearly 70 % of China's industrial emissions.

Core explanatory variable: This paper selects green bonds (*Gb*) as the main independent variable, measured by the total issuance of green bonds divided by the total issuance of all bonds to assess the level of green bond development.

Moderating variable: Environmental regulation (*RE*) is chosen as the moderating variable. It is measured by the ratio of industrial pollution control expenditure to GDP of the secondary industry.

Other Control Variables Selection: Since carbon emissions and carbon intensity are closely related to economic development, it is necessary to control for the heterogeneity of economic development characteristics in both the treatment and control groups to ensure their comparability. The control variables selected for measuring regional economic development heterogeneity include: Renewable Energy (*Ren*), based on research by Dogan and Seker [25], measuring renewable energy development from the perspective of nuclear, solar, wind, and hydroelectric power generation; Innovation (*Cx*), specified as the total number of invention patents; Degree of Openness (*Fdi*), measured by the actual amount of foreign capital used annually divided by GDP; Urbanisation (*Urban*), measured by the ratio of urban population to total population; Per Capita GDP (*Pgdp*), specified as the actual per capita GDP; Marketisation (*Mark*), specified as the total marketisation index; Research and Development Intensity (*Rdi*), measured by R&D expenditure divided by GDP; Industrial Structure (*Is*), measured by the ratio of the tertiary industry to GDP.

Data sources

This study uses a research sample of 30 provinces and autonomous regions in China from 2007 to 2022.

Table 1

Descriptive statistics of variables

Variables	**Sample size**	**Mean**	**Standard deviation**	**Minimum**	**Maximum**
CI [%]	480	0.03	0.02	0.02	0.13
Gb [%]	480	0.12	0.02	0.09	0.16
Ren [%]	480	0.25	0.24	0.00	0.93
Cx [itm]	480	9.60	1.60	5.40	13.20
Fdi [%]	480	14.60	1.70	8.00	17.00
Urban [%]	480	–0.61	0.24	–1.29	–0.12
Pgdp [RMB]	480	10.57	0.57	8.96	12.10
Mark [%]	480	7.68	1.85	3.39	11.56
Rdi [%]	480	0.43	0.59	–0.81	1.88
Is [%]	480	3.83	0.19	3.49	4.46

The data sources include: carbon emission data from the China Carbon Emission Accounts Database, green bond data from the National Bureau of Statistics and CSMAR database; renewable energy data from the "China Energy Statistical Yearbook"; urbanisation data from the "China Population and Employment Statistics Yearbook"; research and development intensity from the "China Statistical Yearbook on Science and Technology"; and other data from sources such as the National Bureau of Statistics) [28]. Due to data limitations, the data mentioned above is only available at the provincial level. Table 1 provides descriptive statistics of the main variables.

Research model

To verify the theoretical analysis of the impact of green bond development on carbon emission intensity discussed earlier, we construct the following bidirectional fixed effects model for regression testing. The specific model construction is as follows:

$$CI_{i.t} = \alpha_0 + \alpha_1 Gb_{i.t} + \alpha_2 Ctrl + \mu_i + \gamma_i + \varepsilon_{it} \tag{2}$$

where: the dependent variable represents the carbon emission intensity of province *i* in year *t*; the core explanatory variable indicates the level of green finance development; and *Ctrl* denotes a series of control variables. μ_i represents individual fixed effects, γ_i indicates time fixed effects, and ε_{it} denotes the random error term.

Construction of the Regulation Effect Model Based on Environmental Regulation. To further verify the moderating effect of environmental regulation on the impact of green bonds on carbon emission intensity discussed above, we incorporate the interaction term of green bonds and environmental regulation (*Gb*RE*) into model (2) to construct models (3) and (4). These models are used to examine the specific role of environmental regulation in the relationship between green bonds and carbon emission intensity.

$$CI_{i.t} = \alpha_0 + \alpha_1 Gb_{i.t} + \alpha_2 RE_{i.t} + \gamma Ctrl_{i.t} + \mu_i + \gamma_i + \varepsilon_{it} \tag{3}$$

$$CI_{i.t} = \alpha_0 + \alpha_1 Gb_{i.t} + \alpha_3 RE_{i.t} Gb_{i.t} + \gamma Ctrl_{i.t} + \mu_i + \gamma_i + \varepsilon_{it} \tag{4}$$

Spatial Durbin Model Construction: Existing research suggests that spatial correlation is often considered when exploring the factors affecting carbon emissions. Ignoring this spatial dependence can lead to biased estimation results. Therefore, to examine the spatial autocorrelation between green finance development and carbon emissions, this paper adopts spatial econometric models to further analyse their intrinsic relationship. Commonly used spatial econometric models include the spatial lag model (SLM, also known as spatial autoregressive model SAR), the spatial error model (SEM), and the spatial Durbin model (SDM). Under certain conditions, the spatial Durbin model (SDM) can transform into the spatial lag model and the spatial error model. This paper constructs a spatial econometric model to study the effect of green finance development on carbon emissions. Subsequently, Wald and LR tests will verify whether the spatial Durbin model (SDM) degenerates into the spatial lag model and the spatial error model.

Choice of Spatial Weight Matrix: Inverse Distance Weight Matrix: Based on the first law of geography, the interaction effect between regions weakens as the distance between them increases. Therefore, the inverse of the distance between spatial units is commonly used to reflect the strength of spatial interaction effects. Similarly, the spatial spillover effect of green bonds on carbon dioxide emissions is more evident in geographical distance. Therefore, drawing on existing research, this paper uses the inverse distance matrix (*W*) to represent the spatial weight matrix between regions.

$$W = \begin{cases} \frac{1}{d_{ij}}, & i \neq j \\ 0, & i = j \end{cases} \tag{5}$$

In the aforementioned equation, $\frac{1}{d_{ij}}$ is the inverse of the geographical distance between regions (*i*) and (*j*). This paper further chooses the matrix of inverse distance squared as a control, where (*d_{ij}*) is zero when (*i \neq j*).

Results

Baseline regression results

Table 2 reports the baseline regression results of the impact of green bonds on urban carbon emission intensity. After controlling for year fixed effects and individual fixed effects, the first column of results in Table 2 indicates that the coefficient of the core explanatory variable, green bonds (*Gb*), is significantly negative. This suggests that the development of green bonds can reduce carbon emission intensity, providing preliminary support for hypothesis H1 of this paper.

Furthermore, to examine the moderating effect of environmental regulation on the impact of green bonds on carbon emission intensity, an interaction term between green bonds and environmental regulation was added to the constructed model (1), resulting in the construction of the moderating effect model (3). The test results presented in columns (2) and (3) of Table 2 show that both the coefficient of environmental regulation and the coefficient of the interaction term between environmental regulation and green bonds are significantly negative. This indicates that environmental regulation has a positive moderating effect on the relationship between green bonds and carbon emission intensity. Implemented environmental regulation policies can provide macro-level guidance for the development of green bonds, such as mandating corporate information disclosure and raising environmental standards. These measures help prevent green funds from flowing into non-green projects, enhance the rational allocation of green bond resources, and fully realise the carbon reduction potential of green bonds.

Table 2

Analysis of baseline regression results

Variables	**(1)**	**(2)**	**(3)**
Gb	$-0.175^{*}(-1.98)$	$-0.186^{*}(-1.97)$	$-0.676^{**}(-2.53)$
RE		$-0.001^{**}(-2.05)$	0.008(1.65)
*Gb*RE*			$-0.082^{*}(-1.85)$
Control variables	YES	YES	YES
Individual	YES	YES	YES
Time	YES	YES	YES
N	480	480	480
r^2	0.946	0.945	0.945

***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively

Spatial econometric model regression results

Spatial autocorrelation test

This paper uses the Moran's *I* index to measure the spatial dependency of carbon emission intensity, with calculations performed using Stata software:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{s^2 \sum_{i=1}^{n}\sum_{j}^{n} W_{ij}} \tag{6}$$

In this paper, $n = 30$, i and j represent spatial units, x is the mean of the variable data, S^2 is the variance, and W_{ij} is the spatial weight matrix.

Moran's I typically ranges from –1 to 1, where positive values indicate positive spatial autocorrelation (spatial clustering) and negative values indicate negative spatial autocorrelation (spatial dispersion). A value of 1 indicates complete spatial clustering, –1 indicates complete spatial dispersion, and 0 indicates random spatial distribution. The results of the spatial dependency test for carbon emissions are shown in Table 3. The global Moran's *I* index for the corresponding years indicates that from 2007 to 2022, the carbon emission intensity, represented under the inverse distance spatial weight matrix, is significant at the 1 % level, showing significant positive spatial autocorrelation and evident spatial clustering characteristics across China's provinces.

Table 3

Moran's *I* for carbon emission intensity in China

Year	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**
Moran's I	0.180	0.219	0.205	0.218	0.224	0.238	0.186
Z-Statistic	2.636	2.824	2.726	2.854	2.945	3.020	2.726
P-Value	0.003	0.001	0.003	0.002	0.002	0.001	0.002
Year	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
Moran's I	0.174	0.162	0.160	0.162	0.170	0.170	0.178
Z-Statistic	2.614	2.514	2.502	2.430	2.560	2.522	2.580
P-Value	0.004	0.005	0.004	0.006	0.004	0.004	0.005
Year	**2021**	**2022**					
Moran's I	0.175	0.176					
Z-Statistic	2.610	2.592					
P-Value	0.004	0.005					

Spatial model regression results and analysis

A hausman test was conducted to choose between fixed effects and random effects for spatial econometric regression, and the test results significantly rejected the null hypothesis at the 1% level, indicating that fixed effects are preferable. Thus, this paper chooses fixed effects. Following the spatial econometric model selection in the second part of the research design, spatial lag model (SAR), spatial error model (SEM), and spatial Durbin model (SDM) regressions were conducted under the inverse distance weight matrix. The Wald test and LR test were also used under the inverse distance squared weight matrix to verify whether the spatial Durbin model (SDM) would degenerate into the spatial lag model (SAR) and spatial error model (SEM).

Table 4 shows that in the spatial lag model (SAR), spatial error model (SEM), and spatial Durbin model (SDM), the impact coefficient of green bonds is significantly negative, indicating that the development of green bonds is beneficial for reducing carbon emissions. The Wald test and LR test results are both significant at the 1% level, further validating that the spatial Durbin model (SDM) should be used to analyse the impact of green bonds on carbon emission intensity. The spatial regression coefficient of the spatial Durbin model under the inverse geographical distance weight matrix is –0.291, which is significant at the 5 % level, indicating spatial effects exist in carbon emission intensity among provinces in China.

Table 4

Regression results of spillover effects of green bonds on carbon emission intensity

Variables	**SAR**	**SEM**	**SDM**
Gb	$-0.156^{*}(-1.92)$	$-0.151^{*}(-1.75)$	$-0.132^{*}(-1.71)$
Ren	$-0.015^{**}(-2.14)$	$-0.014^{*}(-1.96)$	$-0.016^{**}(-2.25)$
Cx	0.003(1.05)	0.002(0.72)	0.003(1.45)
Fdi	0.001(1.64)	0.002(1.45)	$0.001^{*}(1.76)$
Urban	0.002(0.26)	0.003(0.30)	–0.003(–0.23)
Pgdp	$-0.025^{***}(-3.75)$	$-0.020^{**}(-3.35)$	$-0.035^{***}(-5.10)$
Mark	–0.000(–1.29)	–0.001(–1.21)	–0.001(–1.34)
Rdi	$-0.009^{**}(-2.68)$	$-0.008^{**}(-2.38)$	$-0.014^{***}(-3.89)$
Is	$0.022^{**}(3.24)$	$0.023^{**}(3.22)$	$0.017^{**}(2.38)$
Spatial_rho	$-0.325^{**}(-3.19)$		$-0.291^{**}(-2.75)$
Spatial_lambda		–0.172(–1.45)	
Variance_sigma2_e	$0.000^{***}(13.85)$	$0.000^{***}(13.90)$	$0.000^{***}(13.86)$
Wx			
Gb	$-0.155^{*}(-1.82)$		$0.476^{**}(2.35)$
Ren	$-0.015^{**}(-2.25)$		$-0.034^{*}(-1.70)$
Cx	0.002(1.17)		0.000(0.01)
Fdi	$0.001^{*}(1.68)$		$0.006^{**}(2.72)$
Urban	0.002(0.26)		$0.082^{***}(3.42)$
Pgdp	$-0.023^{***}(-3.74)$		–0.016(–1.08)
Mark	–0.001(–1.30)		$-0.005^{**}(-2.56)$
Rdi	$-0.009^{**}(-2.74)$		0.009(1.24)
Is	$0.024^{***}(3.40)$		$-0.035^{*}(-1.86)$
Sample size	480	480	480
R^2	0.416	0.407	0.488

In the spatial Durbin model, the coefficient of the main explanatory variable, the level of development of green bonds, is –0.132, indicating that the development of green bonds can reduce carbon emissions and lower carbon emission intensity. Among the included control variables, the estimation coefficients for renewable energy, per capita GDP, and R&D intensity are significantly negative, suggesting that further economic development, increased R&D investment, and the use of renewable energy can all reduce carbon emissions.

Table 5

Wald and LR tests of spatial econometric panel models

Variables	**SAR**		**SEM**	
Test	Wald test	LR test	Wald test	LR test
Statistic	chi2(9) = 48.78	chi2(9) = 109.85	chi2(9) = 56.25	chi2(9) = 119.98
P-Value	0.0000	0.0000	0.0000	0.0000

Spatial spillover effect decomposition

To more intuitively elucidate the impact of green bonds on carbon emission intensity, the spatial spillover effect is divided into direct and indirect effects, as shown in Table 6. Under the inverse distance weight matrix, the direct effect of the development level of green bonds is negative, while the indirect and total effects are positive, indicating that local development of green bonds reduces local carbon emission intensity but promotes carbon emission intensity in surrounding neighbouring regions. This may arise from differences in the intensity of environmental regulation and policy incentives across different regions, providing polluting enterprises the opportunity to avoid environmental governance through cross-regional relocation, resulting in nearby transfer of polluting industries. Additionally, in the long run, costs associated with environmental regulation may either drive local enterprises to innovate in situ or relocate polluting enterprises to neighbouring areas with weaker environmental regulation. The acceptance of industries by adjacent regions may increase carbon emissions within those regions, meaning local development of green bonds may promote carbon emission intensity in neighbouring areas. In the control variables, the direct effects of renewable energy (*Ren*), urbanization (*Urban*), per capita GDP (*Pgdp*), R&D intensity (*Rdi*), and industrial structure (*Is*) under the inverse distance weight matrix are mostly significantly negative at the 5 % level, indicating that the use of renewable energy, economic growth, increased urbanization, and higher R&D investment all contribute to the reduction of carbon emissions. Moreover, the direct, indirect, and total effects of renewable energy (*Ren*) are all significantly negative, demonstrating that the development of renewable energy not only helps curb carbon emissions locally but also exerts an inhibitory effect on carbon emissions in neighbouring regions.

Table 6

Decomposition of spatial spillover effects of explanatory and control variables

Variables	Direct effect	Indirect effect	Total effect
Gb	$-0.152^{*}(-1.86)$	$0.432^{**}(-2.52)$	$0.282^{*}(-1.66)$
Ren	$-0.016^{**}(-2.15)$	$-0.025(-1.55)$	$-0.038^{**}(-2.44)$
Cx	$0.002(-1.58)$	$-0.001(-0.11)$	$0.002(-0.64)$
Fdi	$0.001(-1.42)$	$0.004^{**}(-2.50)$	$0.005^{**}(-3.13)$
Urban	$-0.006(-0.60)$	$0.068^{***}(-3.45)$	$0.063^{**}(-3.25)$
Pgdp	$-0.032^{***}(-4.89)$	$-0.005(-0.43)$	$-0.038^{***}(-3.70)$
Mark	$-0.001(-1.05)$	$-0.004^{**}(-2.26)$	$-0.004^{**}(-3.01)$
Rdi	$-0.016^{***}(-4.02)$	$0.012^{*}(-1.90)$	$-0.005(-0.51)$
Is	$0.019^{**}(-2.76)$	$-0.035^{**}(-2.18)$	$-0.016(-0.84)$

Robustness test

This paper conducts robustness tests by introducing different spatial weight matrices. In the earlier analysis, the inverse distance matrix (W) was used as the spatial weight matrix. To validate the robustness of the estimates, a geographically proximate spatial weight matrix ($W1$) and a spatial economic distance matrix ($W2$) are introduced to re-estimate the spatial Durbin model.

The adjacency matrix ($W1$) is constructed based on geographical spatial adjacency, where matrix elements consist of 1 and 0. If spatial unit (k) is adjacent to spatial unit (g) (sharing a common boundary or intersection), it is marked as 1; otherwise, it is marked as 0. The specific form is as follows:

The adjacency matrix ($W2$) is constructed based on economic distance, with the specific formula as follows:

$$W1_{kg} = \begin{cases} 1, & \textit{Spatial unit k is adjacent to spatial unit g} \\ 0, & \text{while spatial unit k is not adjacent to spatial unit g} \end{cases}$$

$$W2_{kg} = \begin{cases} \dfrac{1}{\left|Y_k - Y_g\right|}, & \text{if } k \neq g \\ 0, & \text{if } k = g \end{cases} \qquad Y_k = \frac{1}{30}\sum_{t=2007}^{2022} Y_{kt}$$

where k and g represent regions, and Y_k and Y_g represent the per capita GDP of region k and g from 2007 to 2022. If the economic development levels between two regions are more similar, the economic distance is closer, and the spatial dependence effect between the two regions is greater, therefore, the weight is larger.

The robustness test results are shown in Table 7. By introducing the spatial weight matrix ($W1$), the regression coefficient of the explanatory variable in the spatial Durbin regression main effect remains significantly negative, indicating that the development of green bonds helps reduce local carbon emissions. For different spatial weight matrices, the model estimation results remain stable, indicating robustness of the findings.

Table 7

Robustness test

Variables	**(1)**	**(2)**
	$W1$	$W2$
Gb	-0.009^{*} (–1.86)	-0.015^{**} (–1.98)
Control variables	YES	YES
Regional fixed effects	YES	YES
Year fixed effects	YES	YES
R^2	0.435	0.438
N	480	480

Discussion

Based on the findings from this study, several important insights emerge regarding the role of green bonds in achieving regional low-carbon development goals. The analysis demonstrates that green bonds are an effective tool for reducing carbon emission intensity, which is essential for meeting China's dual carbon development objectives. However, the study also uncovers a complex dynamic in how green bonds impact carbon emissions at the regional level, particularly when considering the spatial spillover effects. Firstly, the significant reduction in carbon emission intensity at the local level, as observed in the results, highlights the effectiveness of green bonds in directing capital towards environmentally friendly projects. This supports the notion that green finance can play a crucial role in the transition to a low-carbon economy by encouraging investment in renewable energy, energy efficiency, and other sustainable initiatives. The robustness of these findings under the Spatial Durbin Model further reinforces the reliability of the results and confirms the importance of green bonds as a policy tool for carbon reduction.

However, the decomposition of the total effect reveals a noteworthy and concerning trend: the relocation of polluting enterprises to neighbouring regions. This phenomenon suggests that while green bonds reduce carbon emissions locally, they may inadvertently contribute to the transfer of pollution across regional boundaries. The varying intensities of environmental regulations and incentive policies across provinces create an uneven playing field, where regions with stricter policies benefit from reduced carbon emissions at the expense of their neighbours. This inter-regional spillover effect poses a challenge to the overall objective of national carbon reduction and highlights the limitations of a regionally isolated approach to green finance. In light of these findings, it is clear that while green bonds are effective in promoting carbon reduction, they must be implemented within a broader, coordinated framework to avoid unintended consequences. The study emphasises the need for enhanced communication and cooperation among provinces to harmonise environmental regulations and incentive structures. By breaking down regional barriers and fostering a collaborative approach to green finance, it is possible to mitigate the negative spillover effects and achieve a more balanced and equitable reduction in carbon emissions across all regions. Moreover, the findings suggest that policymakers should consider the spatial dynamics of carbon emissions when designing green bond policies. A more holistic approach, which includes mechanisms to manage the relocation of polluting enterprises, could prevent the displacement of environmental burdens and ensure that all regions benefit from green bond initiatives. This could involve the establishment of inter-provincial agreements, shared environmental standards, and joint incentive programs that align the goals of green bonds with the broader national objectives of carbon reduction.

To sum up, while green bonds offer a promising pathway to reducing carbon emissions, their success at the regional level depends on a coordinated approach that considers the spatial implications of environmental policy. Future research should explore these dynamics further, particularly in the context of different regional policy frameworks, to develop more effective strategies for achieving nationwide low-carbon transformation.

Conclusion

This study offers valuable insights into the role of green bonds in reducing carbon emission intensity across China's provinces, illuminating both the advantages and challenges of their implementation. The findings affirm that green bonds serve as a potent instrument for promoting low-carbon development, particularly by directing investments towards environmentally sustainable projects. Our analysis demonstrates that green bonds can significantly diminish carbon emissions at the local level, underscoring their importance in China's pursuit of its dual carbon development goals.

However, the study also reveals a critical issue: unintended spatial spillover effects. While green bond implementation reduces local carbon emissions, it can inadvertently lead to the relocation of polluting enterprises to neighbouring regions. This displacement of environmental burdens undermines the overall efficacy of green bonds at the national level, highlighting the necessity for a more coordinated approach to green finance.

To maximise the positive impact of green bonds, addressing these inter-regional spillover effects through enhanced provincial collaboration is essential. Harmonising environmental regulations and incentive policies across regions can prevent the uneven distribution of pollution and ensure a more equitable reduction in carbon emissions.

Furthermore, policymakers should consider the spatial dynamics of carbon emissions when designing and implementing green bond policies. By incorporating mechanisms to manage the relocation of polluting activities, it is possible to avoid the displacement of environmental impacts and ensure that green bonds contribute effectively to reducing carbon intensity across all regions.

In conclusion, to strengthen the green bond market, enhance information disclosure by establishing a mandatory system. Integrate environmental disclosure requirements into the evaluation processes for green products and investments. This ensures funds are used for genuine green projects, prevents "greenwashing", and regulates the green bond market. Strictly review green bond issuance and usage to ensure they meet environmental standards, enhancing market transparency and credibility.

Tailor green bond policies to regional differences based on financial marketisation and environmental regulation. Leverage green bonds to complement and enhance environmental regulations. Advance financial reforms to ease financing constraints on green technologies, boost green finance, and raise the proportion of direct financing in green investments. Create cross - regional cooperation mechanisms to eliminate barriers, coordinate environmental regulations, and prevent the relocation of polluting firms. Unify environmental standards and supervision to reduce regional policy disparities and avoid carbon leakage.

Future research should deeply explore how international green finance mechanisms impact global carbon reduction and industry shifts, and how China can participate in and promote international green finance cooperation for broader environmental benefits. It should also analyse the long - term effects of green finance policies, especially on industry relocation and regional economic model changes, and explore policy optimisations for sustainable development.

References

[1] Zhang Q, Sun Y. Real-time pricing model of smart grid under dual-carbon target based on social welfare maximisation. Economic Computation Economic Cybernetics Stud Res. 2024;58(2):299-313. DOI: 10.24818/18423264/58.2.24.18.

[2] Xu W, Xu S, Liu DY, Awaga AL, Rabia AC, Zhang YY. Impact of fairness concerns on resource-sharing decisions: A comparative analysis using evolutionary game models in manufacturing enterprises. Adv Prod Eng Manage. 2024;19(2):223-38. DOI: 10.14743/apem2024.2.503.

[3] Rajunčius M, Miečinskienė A. Measuring the Impact of payment innovations in sustainable finance: A refined framework for evaluating ESG, social equity, financial inclusion and efficiency. J Manage Changes Digital Era. 2024;1(1):31-41. DOI: 10.33168/JMCDE.2024.0103.

[4] Sharma P, Karki D. Blockchain technology in the digital era: global research trends and financial innovation. J Manage Changes Digital Era. 2025;2(1):93-109. DOI: 10.33168/JMCDE.2025.0107.

[5] Gasparatos A, Doll C, Esteban M, Olang TA, Ahmed A. Renewable energy and biodiversity: implications for transitioning to a green economy. Renew Sust Energy Rev. 2017;70:161-84. DOI: 10.1016/j.rser.2016.08.030.

[6] Liu T. Time-varying influence of policy risk on carbon emissions analysis. J Service Innov Sust Development. 2024;5(2):95-115. DOI: 10.33168/SISD.2024.0206.

[7] Lu C, Wang K. Natural resource conservation outpaces and climate change: Roles of reforestation, mineral extraction, and natural resources depletion. Resources Policy. 2023;86(B):104159. DOI: 10.1016/j.resourpol.2023.104159.

[8] Rinkevičius T, Miečinskienė A. Assessment of the involvement of the European Union countries in sustainable finance. J Service Innov Sust Development. 2023;4(1):115-28. DOI: 10.33168/SISD.2023.0110.

[9] Wu CH, Tsai SB, Liu W, Shao XF, Xia YK, Wacławek M. Green environment and sustainable development: methods and applications. Ecol Chem Eng S. 2021;28(4):467-70. DOI: 10.2478/eces-2021-0030.

[10] Liu W, Tsai SB, Wu CH, Shao X, Wacławek M. Corporate environmental management and sustainable operation: theory and application. Ecol Chem Eng S. 2022;29(3):283-5. DOI: 10.2478/eces-2022-0020.

[11] Khadka P, Karki D, Dahal R, Khanal D. Mapping the landscape of green finance and banking performance research: a bibliometric analysis. J Service Innov Sust Development. 2024;5(1):176-93. DOI: 10.33168/SISD.2024.0110.

[12] Li J. The mechanism and path of finance promoting the development of low carbon economy. Ecol Chem Eng S. 2023;30(2):227-34. DOI: 10.2478/eces-2023-0023.

[13] Zhou C, Qi S, Li Y. Do green bonds restrain corporate financialization? Environ Eng Manage J. 2023;22(3):439. DOI: 10.30638/eemj.2023.034.

[14] Ren S, Li X, Yuan B, Li B, Chen X. The effects of three types of environmental regulation on eco-efficiency: A cross-region analysis in China. J Cleaner Prod. 2018;173:245-55. DOI: 10.1016/j.jclepro.2016.08.113.

[15] Dyadik N, Chapargina A. Business and government: environmental and economic responsibility in the Russian Arctic. Arctic North. 2020;41:33-52. DOI: 10.37482/issn2221-2698.2020.41.38.

[16] Shangguan X, Wang X. Tax competition, environmental regulation and air pollution-empirical evidence from 278 cities in China. Environ Eng Manage J. 2021;20(4):635-44. DOI: 10.30638/eemj.2021.062.

[17] Wu SH, Wang HQ, He M, Qin C. Environmental regulation, environmental policy complexity and technological innovation efficiency. Ecol Chem Eng S. 2023;30(2):159-66. DOI: 10.2478/eces-2023-0015.

[18] Li R, Sun T. Research on impact of different environmental regulation tools on energy efficiency in China. Polish J Environ Stud. 2020;29(6):4151-60. DOI: 10.15244/pjoes/120520.

[19] Lin Z, Wang W. How can differentiated informal environmental regulations contribute to pollution reduction in China. Environ Eng Manage J. 2022;21(11):1847-63. DOI: 10.30638/eemj.2022.164.

[20] Güçlü M, Korkmaz T. Comparative politics of international environmental agreements and the EU. Economic Computation Economic Cybernetics Stud Res. 2024;58(1):213-28. DOI: 10.24818/18423264/58.1.24.14.

[21] Li X, Yu D, Yu J. Spatial spillover effect of heterogeneous environmental regulations on carbon productivity-spatial Durbin model. China Soft Sci. 2020;4:82-96. DOI: CNKI:SUN:ZGRK.0.2020-04-008.

[22] Zhu X, Li B. Study on spatial econometrics of environmental governance efficiency of provincial fiscal policy in China. Proc 2019 10th Int Conf E-Business, Manage Economics. 2019;12-20. DOI: 10.1145/3345035.3345070.

[23] Wang C, Chu Z, Gu W. Assessing the role of public attention in China's wastewater treatment: A spatial perspective. Technol Forecasting Social Change. 2021;171(10):120984. DOI: 10.1016/j.techfore.2021.120984.

[24] Wu L, Yang M, Wang C. Strategic interaction of environmental regulation and its influencing mechanism: Evidence of spatial effects among Chinese cities. J Cleaner Prod. 2021;312(8):127668. DOI: 10.1016/j.jclepro.2021.127668.

[25] Dogan E, Seker F. Determinants of CO_2 emissions in the European Union: The role of renewable and non-renewable energy. Renew Energy. 2016;94(8):429-39. DOI: 10.1016/j.renene.2016.03.078.

[26] Zhou W, Wu X, Zhao G. An empirical study on the effect of green finance on carbon emission reduction under the "dual carbon" goal. J Hebei Univ Economics Business. 2024;45(1):47-58. DOI: 10.14178/j.cnki.issn1007-2101.20231108.005.