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Does Green Building Development Reduce Carbon Emissions? Mechanisms and Spatial Spillover Effects Across Chinese Provinces

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Abstract

The construction sector's chronic high energy consumption and carbon emissions make decarbonization an urgent priority for China, yet the precise mechanisms through which the green building industry (GBI) reduces carbon emission intensity remain poorly understood. This study constructs a comprehensive assessment indicator system to measure GBI development across 30 Chinese provincial regions from 2012 to 2020, and employs a two-way fixed-effects panel model alongside the Spatial Durbin Model (SDM) to identify both the magnitude and the spatial dimensions of GBI's carbon reduction effects. The main findings are as follows. First, GBI development significantly reduces regional carbon emission intensity, but substantial spatial imbalance exists — coastal provinces consistently outperform their inland counterparts, mirroring China's broader east–west economic gradient. Second, mechanism analysis reveals a dual transmission pathway: GBI lowers energy consumption intensity (an efficiency effect), while rising local investment intensity — proxied by FDI — generates a crowding-out effect that suppresses GBI scale and partially offsets its emission reduction contribution. Third, spatial autocorrelation analysis confirms significant positive spatial clustering in both carbon emission intensity and GBI development level. Spatial Durbin Model estimates further reveal that, under the economic-geographic weight matrix, GBI development in economically advanced regions triggers carbon emission transfers toward less developed neighboring regions — a spatial spillover pattern consistent with China's gradient economic development model. The spatial lag terms of local investment intensity and energy consumption intensity are also significantly positive, indicating that increases in these variables drive carbon emission agglomeration and diffusion across provincial borders. These findings collectively suggest that market-oriented investment alone cannot deliver adequate emission mitigation, and that policy reforms correcting investment bias, strengthening environmental regulation, and fostering coordinated regional green development are essential to fully unleashing GBI's carbon reduction potential in China's pursuit of carbon peak and carbon neutrality goals.

1 Introduction

The construction sector is one of the most energy-intensive and carbon-intensive industries in the global economy. Throughout its entire supply chain — from raw material manufacturing and equipment-driven construction processes to the maintenance and operation of completed buildings — enormous amounts of energy are consumed and greenhouse gases (GHGs) are released (Huo et al., 2020; Lu et al., 2026). In China's case, conventional construction methods account for approximately 40% of global energy consumption. The industry as a whole consumes nearly 20% of total societal energy and contributes roughly 36% of global GHG emissions (Zhong et al., 2021; Hussain et al., 2025). More strikingly, the per-square-meter energy consumption of Chinese construction projects is approximately three times higher than that of developed countries (Zhang et al., 2019; Chen et al., 2020; Xu et al., 2026), underscoring the urgent need for structural transformation in this sector.

Against this backdrop, the green building industry (GBI) has emerged as a critical strategic response. Since the early 21st century, China has progressively established a policy framework supporting GBI development, encompassing the National Green Building Innovation Award, the 14th Five-Year Plan, and sector-specific regulations issued by ministries ranging from the National Development and Reform Commission to the Ministry of Ecology and Environment (Deng et al., 2025; Iqbal et al., 2025). Local governments have further supplemented central directives with province-level evaluation systems and supporting measures, propelling the GBI into a new stage of comprehensive development. By 2021, China's green building market had reached approximately RMB 2.2 trillion in scale. As an emerging green industry, GBI is now regarded as indispensable to China's pursuit of high-quality, low-carbon development (Khan et al., 2019; Wang et al., 2025).

Despite this growing policy emphasis, two fundamental questions remain largely unresolved. First, although it is broadly recognized that GBI contributes to emission reduction, the quantitative magnitude of its effect on regional carbon emission intensity — and how this effect varies across regions — has rarely been rigorously assessed. Second, and more critically, the internal mechanisms through which GBI achieves carbon reduction remain a "black box." Prior studies have primarily focused on engineering-level analyses of individual projects (Ghaffarian et al., 2013; Wong and Zhou, 2015; Pal et al., 2017), cost–benefit evaluations (Ding et al., 2018), and life-cycle assessments (Pierucci et al., 2018), without systematically investigating the macro-level pathways — particularly the roles of investment structure and energy efficiency — through which GBI development translates into aggregate emission outcomes.

A third, previously neglected dimension concerns spatial interdependence. Carbon emissions do not respect provincial boundaries; they diffuse and cluster across geographic and economic space (Li and Wang, 2022; Fang et al., 2025; Zhou et al., 2023). Relying solely on non-spatial models to evaluate GBI's emission reduction effects therefore risks estimation bias and fails to capture whether the carbon reduction achieved in one region simply displaces emissions to neighboring areas. This spatial spillover dimension is particularly consequential given China's pronounced regional economic heterogeneity: under the "core-periphery" spatial development pattern, green building development in economically advanced regions may drive investment and energy-intensive activities toward less developed neighbors, generating unintended spatial spillovers of carbon emissions.

To address these gaps, this study makes three principal contributions. First, we construct a comprehensive assessment indicator system covering both the vertical industrial chain of GBI and its horizontal supporting industries, and use it to evaluate GBI development levels across 30 Chinese provincial regions from 2012 to 2020. Second, using a two-way fixed-effects panel model, we identify the direct carbon reduction effect of GBI development and unpack the dual transmission mechanism: an energy efficiency channel (through reduced energy consumption intensity) and an investment crowding-out channel (through FDI-driven preference for traditional high-carbon industries). Third, we extend the analysis to the spatial dimension by constructing Spatial Durbin Models under three spatial weight matrices — adjacency, geographic distance, and economic-geographic — to examine the spatial spillover effects of GBI's carbon reduction and to reveal the spatial mechanisms through which local investment intensity and energy consumption intensity propagate carbon emissions across provincial borders.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the methodology, including the GBI assessment framework and econometric specifications. Section 4 reports the empirical results, covering the carbon reduction effects, mechanism analysis, spatial autocorrelation, spatial spillover estimation, and robustness checks. Section 5 concludes with policy recommendations.

2 Literature review

2.1 The relationship between green buildings industry and CO2 mitigation.

As one type of human activity, resource consumption and environmental impacts caused by the construction and operation of buildings account for quite considerable proportions (Khan et al., 2019; Ismail and Zokm, 2025). According to research findings, our construction sector has already consumed nearly half of all the energy on earth (about 40%), while approximately 33% of worldwide greenhouse gas emissions have been attributed to construction-related actions (Chau et al., 2015). That’s why, beginning from the 1990s, there has been a huge growth of the green building industry. It means reducing its own resource usage, decreasing adverse effects toward the environment. At the same time, it needs to provide us humans with healthy, comfortable, and efficient space for habitation and work. In this way, both human beings and nature can live in peace (Zhang et al., 2023; Li, 2025).

From the point of view of industrial economy, the green building industry belongs to one sort of green industry, while their concepts and meanings are quite close to each other along with the further understanding of sustainable development (Burton, 1987; Nejat et al., 2015). In comparison with the conventional building industry, the green building industry can be regarded as the recently-born sector, represented by saving energy, reducing emissions, decreasing consumption, etc. Meanwhile, this kind of sector has run through every link of the entire chain of the construction industry, including upstream, middle-stream, and downstream. Therefore, whether they have environmental protection properties would be used as criteria when defining green building industries, so that they will meet almost all existing understandings about green industries at present (Li et al., 2014; Zhou et al., 2025).

Green buildings: one possible answer is because its total environmental and economic benefit level is better than ordinary construction industry (Chen et al., 2020). Researchers have studied the energy-saving and emissions reduction effects of the green building industry through different angles, including the cost of green building (Ding et al., 2018), its own energy efficiency (Ghaffarian et al., 2013), and sustainable development of the entire life cycle process (Wong and Zhou, 2015). Some researchers carried out quantitative analysis about the regional features of green building industry development (Lu et al., 2020), planning of industrial development (Li et al., 2014; Zhang et al., 2018; Hu et al., 2025), and industrial chain construction (Julie, 2019). But only some studies have studied the development process of the construction industry according to LCA (Life Cycle Assessment) so far (Pal et al., 2017; Pierucci et al., 2018). However, these methods are just concentrating on calculating how much amount of CO2 has been emitted from the conventional construction industry, without discussing whether developing green building industry can reduce the total CO2 emissions or not. Up till now, there is only one study carried out by Liao and Li (2022), who try to estimate what kind of impact will be brought about through developing green building industry under a footprint framework, but failed to explore which factors could affect the carbon reduction effect of the green building industry.

2.2 The Influencing Factors of Carbon Emission in the Green Buildings Industry.

The growth of the green building sector helps cut carbon emissions. However, how much they can reduce them depends heavily upon several kinds of technology as well as policy support, etc. etc. There has been little research into what kind of circumstances allow us to achieve the carbon-cutting benefits of green buildings. Therefore, this study mainly uses some literature about the construction industry to look for the related theory, method, and indicators. In terms of which factors affect carbon emissions in the construction sector, there are four types of analysis methods which mainly concentrate on them: Kaya identity, LMDI, STIRPAT, and economic model. Xu et al. (2014) believe that the economic output effect based on the LMDI method is the one that affects carbon emissions most among all driving factors of carbon emission in the construction industry, while reducing energy consumption intensity will have great significance to curb the rising trend of carbon emission intensity. Teng et al. (2016) came up with almost the same conclusion according to their econometric models. Fan and Lei (2017) used an extended version of Kaya's decomposition method to identify major influencing factors of carbon emissions in China's construction industry. In their view, carbon emissions are mainly affected by energy consumption structure and energy use efficiency. Wang and Salman (2023) researched the different degrees of carbon emission efficiency between the construction sector and non-construction sector in China through a dual fixed-effect panel data model. They discovered that carbon emission efficiency was quite poor in the construction industry.

As for what factors affect carbon emissions in construction, there have been some common opinions among mainstream international researchers, which put emphasis on engineering aspects (Zou and Couani, 2012; Meadows et al., 2018). While Subramanyam (2017) and Valle et al. (2025) did energy modeling scenario analysis in their study, they predicted the future potentials of saving energy and reducing greenhouse gas emissions in residential sectors, especially when it comes to air conditioning/heating/cooling systems, water heaters, house appliances, and lighting systems, etc. They suggested that almost all (>80%) of emission reductions in the construction sector could be realized via clean technologies' means. Furthermore, Yuan et al. (2017) also highlighted the large existing stock of traditional buildings as one of the main obstacles to green building business development. In order to update/build green buildings, we need further technological innovation so as to improve the stock and help us move/transition away from traditional construction towards developing the green building industry.

When talking about the economic, social, and policy factors of carbon emission in the construction industry, Ahmad (2025) adopted the method of a System Dynamics (SD) model to simulate the amount of CO2 emission produced by residential buildings, which suggests that raising tax on developers of traditional building methods will be able to decrease carbon emission. Labaran et al. (2024), taking residential buildings in Britain as an example, prove the efficiency of all kinds of energy-saving policies when it comes to decreasing energy consumption/carbon emissions that will happen in residential buildings. Kumar et al. (2025) applied externality theory and discovered that enhancing command and control type environmental regulation over the traditional construction industry, while increasing incentives for clean production technologies, has already achieved some effect on decreasing the environmental negative externality created by the traditional construction industry, etc. In accordance with formal institutions theory, Zhou and Lin (2025) also believe that government fiscal-tax incentives policy is able to promote private capital's investment in building's energy-saving market.

Starting from the point of view of informal institution theory, Roh et al. (2018) studied about what effects of GHG emission reduction could have had brought forth by Korean green building certification system. With regards to optimal decision-making theories as well as multiple objective optimisation models, Song et al.(2018) examined the possibility of obtaining necessary amount of carbon emission reduction in construction sector with lowest increase of cost, which proved that government environmental policies and business corporation's social responsibilities would affect construction companies'energy saving and emission reduction strategy; however, they didn't pay much attention to point out its key position in emission reductions in construction industry. Starting out from construction industry stakeholder's angle, Xue et al. (2019), through means of linear programming analysis, explored how carbon tax might impact carbon emission of construction sector, whose conclusion suggested that optimum carbon price was confined by environmental costs and business' emission reduction costs.

So, whether we can realize the above-mentioned carbon reduction effect in the green building sector relies upon various reasons, such as policy, environment, and investment, etc. At present, most studies have explained how they reduce emissions through projects' engineering designs, costs, and benefits. However, they overlook/don't pay attention to/ignore some important macro-factors/variables.

2.3 The mechanism of reducing CO2 emissions in green buildings.

However, there haven't been any studies specifically looking at what mechanisms cause reductions in emissions when the green building sector develops. Nevertheless, because the green building sector belongs to one type of green industries; thus, the fundamental problem it faces during development would also be the conflict between economic growth and environmental protection (Julie, 2019). Hence, we could refer to some rules about investment, energy use, and carbon dioxide emission in environmental economics to analyse how the green building sector brings about a decline in carbon emissions.

In addition, some existing research has described their inherent realization mechanism of carbon reduction effect from another angle – exploring why there is such a serious scale shortage problem in the green building industry through an indirect way. Green et al. (2012), Zaid et al. (2017), Kahn (2019), and Chen et al. (2024) used cases of the USA, Malaysia, etc., to prove that R&D investment level and technology upgrade can impact green buildings' performance and thus the entire development situation of the green building industry through their studies on green building industries across various countries. But we need to pay attention to that, according to what was told by Tiza et al. (2022). Because of relatively cheaper costs compared with traditional ones, the traditional construction industry will have a certain appeal towards investments, which might make the scale of the green building industry smaller and thereby limit their capability of realizing the aforementioned carbon reduction effect. Meanwhile, as mentioned by Akin and Akin (2025), although they are quite environmentally-friendly, the high cost required for investment (especially those technological changes) as well as many uncertainties involved in them also prevent them from being recognized/accepted by mainstream investors. Several classical environmental economic theories can explain this phenomenon as follows: Foreign direct investment (hereinafter referred to as FDI) occupies a considerable proportion among all kinds of investments within China's construction industry; many previous studies have already proved that FDI's influx in China will certainly cause "the pollution haven" effect (Bu and Genin, 2025), which means FDI would choose to invest more in some regions whose level of regulation is relatively low (Qiu et al., 2021); In addition, foreign capital invested into construction industry prefers traditional construction which costs less money than other types; therefore, it has higher carbon emission intensity (Wang and Shao, 2023); furthermore, since there is little room left for further development inside construction industry itself , when the size of traditional construction has expanded, it may generate crowding-out effect so as to restrict the expanding of green buildings' scale while reducing their ability to cut down greenhouse gas emissions caused by human beings at the same time ; thus, the fact that investment intensity rises could crowd out the scale of green building industry is also one of the mechanisms which limits its ability to reduce carbon emission.

In addition, compared with traditional construction industries, green buildings also have lower energy consumption intensity of the construction industry value chain, which will have some carbon reductions. Cheng (2024) measures the total factors productivity of the Australian construction industry, which also includes energy factors, by the means of the Malmquist approach. They discover that the degree of dependence on energy input will have an obvious impact on green total factors production efficiency of the construction industry. And Liu et al. (2018), using the development of world construction industry trade and extension of the global construction industry value chain as two entry points, discuss the relationship between the construction industry and energy change according to the multi-region input-output methodology. The research shows that during 1999-2009, most of the energy requirements in the construction industry are concentrated in intermediate goods, which form a huge amount of indirect and hidden carbon emissions. In a word, the construction industry has always been one of the main energy-consuming sectors, therefore it contains great possibilities for reducing carbon emissions. Therefore, developing the green building industry itself, lowering energy consumption intensity of the construction industry so as to achieve the purpose of reducing carbon emissions is also one of the carbon reduction mechanisms of the green building industry.

2.4 Literature gaps

To sum up all the above-mentioned literature review, we find that although there have been quite a lot of researches about the construction industry, those concerning green building started comparatively later. Among them, research about how the green building industry affects carbon emissions is very few; moreover, there has been almost no study discussing how it works to reduce emissions at present stage.

Worldwide, there is great emission of carbon gas and occurrence of greenhouse effect because of the process of producing/building materials/buildings, and so on (viewed as whole chains). But in fact, the green building industry has great potential for reducing emissions, for itself carries some intrinsic advantages like technology upgrade, low energy consumption, etc. Nevertheless, current investigations mainly focus on analyzing their emission-reducing impacts from the angle of engineering. Therefore, they ignore that the major impact factors at macro level play a very important role in reducing carbon emission capacity of green building industry.

Besides, the present literatures cannot explain too much about the mechanism of carbon reduction in the green building sector, so their emission reduction effect is like "black-box". And there are some research results to verify its basic mechanism.

Industry scale effects: The share of the green building industry within the overall industrial structure may vary due to investments made into conventional industry sectors in the same region. This results in a crowding-out effect against developments in the green building industry.

Technical level of the green construction industry: which can be represented as energy consumption intensity. As technology increases, the energy consumption intensity of green construction industries would go down even more, thus creating more carbon emissions reductions.

Therefore, on this basis, there would build up one kind of double-track mechanism analysis framework, so as to clarify what kinds of ways the green building industry could reduce carbon emissions through its development, etc. In brief, our purpose is to try to explore how China's green building industry can obtain carbon reduction via analyzing such kinds of mechanisms when developing itself, meanwhile assessing their levels of development, and then make some suggestions so that they can provide some references for supporting the green development of the construction industry.

3 Methodology

3.1 Assessment on Development Level of Green Building Industry.

The scale of China's green building industry keeps growing larger, and its market size had reached approximately RMB 2.2 trillion by 2021. Obviously, the green building industry plays an ever-more important position in China's green economic development now. But researches concerning the green building industry have never assessed the developing situation of the green building industry at the regional level before, so they can hardly offer us solid proof to help us know about regional disparities in the development of China's green building industry better either. At the regional difference angle, all kinds of regions have been pushing forward some subsidy policy and supporting measure for green building industry's development actively as well, but what these regions get differs greatly. Besides, too much dependence upon subsidies means that currently, the green building industry cannot shake off policy support yet, and hasn't developed into something that follows market rules either. Hence, getting an objective grasp of what imbalance in the development of the green building industry exists and where there's a shortage of driving force would be something we simply can't avoid coming face to face with when we want to make some green change in our construction industry.

When assessing the developmental status quo of the green building industry, we make up such an index system according to Lu et al.'s (2020) and Abdel et al.'s (2021) framework, which covers two perspectives: the vertical industrial chain of the green building industry itself and the horizontal supportive industry chain. See details in Table 1. And our information about green building rating comes from the China Green Buildings Database run by MOHURD.

Table 1. Development Level Evaluation Indicators and Corresponding Weights of Green Building Industry

Primary Indicator	Secondary Indicator	Unit
Absolute development level of the green building industry (0.5)	Per capita green building area (0.15)	m²/person
	Number of green building labeled projects (0.15)	/
	Proportion of 2-star and above green building projects (0.08)	%
	Number of operational labeled green building projects (0.08)	/
	Number of high-level institution labeled projects (0.04)	/
Supporting level of the green building industry chain (0.5)	Per capita regional gdp (0.10)	billion yuan/person
	Added value of the construction industry (0.15)	billion yuan
	R&d investment (0.04)	billion yuan
	Added value of the real estate industry (0.06)	billion yuan
	Total output value of non-metallic mineral products industry (0.15)	billion yuan

Note(s): Here we do not provide explanations about what each indicator exactly measures due to space constraint; more information could be found in Lu et al. (2020), Abdel et al. (2021). Weightage mentioned above [inside brackets] comes from Lu et al. (2020), which is calculated based on assessments made by many professionals working in related industries – therefore, it has a strong scientific basis.

In addition, to eliminate the dimensional difference of each indicator, we adopt the z-score method, which is formulated as follows (equation 1):

$$x'_i = \frac{(x_i - \bar{x})}{\sigma} \tag{1}$$

where x'_i is the dimensionless value of a secondary indicator for province i in the green building industry evaluation indicator system; x_i is the original value of the corresponding indicator; $\bar{x}$ is the mean of the original values of the indicator for all provinces; and σ is the standard deviation of the corresponding indicator. After standardization, each indicator score is multiplied by its weight value, and the weighted sum is used to obtain the development level score of the green building industry for each province, as expressed by equation (2):

$$S = \sum_{i=1}^{10} x'_i \times \lambda_i \tag{2}$$

where S is the comprehensive score evaluating the development level of the green building industry for a provincial administrative region, and λ_i is the indicator weight.

3.2 Econometric model

The above describes how we will build an econometrics model to find out the effect of developing green buildings on carbon emissions. Among these variables, our dependent one will be represented by carbon emission intensity, while our main independent variable would represent how developed our green building sector is. Then, since there are other factors that affect carbon emissions too, we have also included some control variables. Based upon this approach, we constructed the following kind of two-way fixed effects panel model:

$$CE_{it} = \alpha + \beta GB_{it} + \sum_{j=1}^{k} \delta_j X_{it,j} + \mu_i + \eta_t + \varepsilon_{it} \tag{3}$$

Where CE_{it} represents the carbon emission intensity of region i in year t, GB_{it} represents the evaluation result of the green building industry development level of region i in year t, and $X_{it,j}$ represents a series of key control variables affecting the carbon emission intensity of the region. $\alpha\alpha$ is the constant term, μ_i is the individual fixed effect coefficient, η_t is the time fixed effect coefficient, and ϵ_{it} is the random error term.

Then, based on equation (3), we add two more interaction terms into it, which aims at testing how the developmental level of the green building industry promotes CO2 emission reduction. Model's exact expression is as below:

$$CE_{it} = \alpha' + \beta' GB_{it} + \beta_1 \overline{GB_{it}} \times \overline{HPI_{it}} + \beta_2 \overline{GB_{it}} \times \overline{ECI_{it}} + \sum_{j=1}^{k} \delta_j X_{it,j} + \mu_i + \eta_t + \varepsilon_{it} \quad (4)$$

Where HPI_{it} represents the local investment intensity of region i in year t. Following the approach of Sijabat (2023), it is measured as the FDI as a percentage of GDP to represent local investment intensity. ECI_{it} represents the energy consumption intensity of region i in year t. It should be emphasized that $X_{it,j}$ represents a series of variables affecting the carbon emission intensity of the region, including the above two mechanism variables. Therefore, since the main effects of the primary variables—green building industry development level, local investment intensity, and energy consumption intensity—are retained in the model, the two interaction terms are mean-centered to avoid multicollinearity issues (Fitzgerald, 2022). The meanings of other variables, the dual fixed effects, and the random error term are as previously described.

3.3 Variable selection and data description

Carbon emission intensity (CE) is used as the dependent variable. CE refers to the amount of carbon emissions for every unit of regional GDP. In this study, we look at how carbon emissions relate with the growth of the green building sector through carbon emission intensity (amount of CO2 emitted for each unit of GDP). We chose not to examine carbon emission density (the number of CO2 emissions produced on average per person), because carbon emission intensities can give us more information about why there is such a big difference in the level of carbon emissions among Chinese provinces since their industrial structures and natural resources are very different.

The independent variables contain our main variable (i.e., the development level of green buildings GB), plus some mechanism variables which come from green development theories and pollution haven theory. Green development theories mainly stress that we need to achieve more effective resource allocation/use as well as cleaner technology/production methods when transforming into a greener industry. Energy intensity, which is one major indicator describing how much energy is used in the production process, can represent the decrease of carbon emissions brought about by the green buildings through intensifying/efficiency improving their energy usage pattern. Pollution haven theory pays attention to people's tendency/predilection towards highly polluting production activities because of the path dependence of traditional investments. Although green building has been relatively cleaner than the conventional construction industry, its high cost might prevent normal investors from entering the market. Hence, investment preferences could possibly limit the scale of green building, which further reduces its carbon abatement effect. Definition is specifically listed below:

Mechanism Variable 1 - Local Investment Intensity (HPI): Local investment intensity reveals market-driven investment intensity. Due to the motivation of local governments to intervene in local investment preferences under China’s decentralization system, the conventional total social investment figure fails to reflect market-oriented investment preferences accurately (Lu et al., 2024). Foreign direct investment (FDI), with its “voting with feet” location selection market mechanism, is used to represent market-oriented investment intensity and is denoted as HPI. HPI can promote economic growth, but given the current development model, investment expansion often signifies more active production activities, leading to increased carbon emissions under the current high energy consumption model (Wang et al., 2024). Additionally, considering environmental regulations, HPI may follow either the pollution haven or pollution halo hypothesis. In regions with lower regulatory levels, HPI may exacerbate local carbon emissions.

Mechanism variable: 2-Energy Consumption Intensity (ECI). According to many studies' findings, we express energy consumption intensity with energy consumption divided by GDP, as mentioned in much literature about energy economics. And as mentioned in our above discussion about mechanisms, ECI is one of the major indicators impacting the level of regional carbon emissions; in addition, it works as another important mechanism variable for green buildings compared to buildings constructed with traditional methods of construction when green buildings want to reduce carbon emissions.

The control variables choose out of four types of factors: policies, endowments, structural factors, and technologies. Within these:

Policy dimension: Environmental Regulation Intensity (ER):

Endowment dimensions: Energy endowment (EC)； Economic scale (GDP); Scale of population (POP).

Structural factors: ECS and IS.

Technical dimension: Degree of technology development (TDC)

Environmental regulations (ER). First of all, environmental regulations might put some kind of pressure on businesses so that they have to develop their technology so as to decrease carbon emission intensity. Secondly, environmental regulations also could push high-emission companies out of this market, therefore lower carbon emissions (Wang et al., 2023). And then, we measure how strongly regulated this province's environment is by counting the occurrence rate of some particular phrases related to 'environment' in those provincial governments' annual reports (Yu et al., 2023).

EC: measured according to the amount of remaining technically recoverable proven reserves of coal, oil and natural gas. Areas with sufficient resources are prone to an extensive mode of economic development, usually favouring high pollution and energy consumption industries therefore, resource endowment could both directly and indirectly affect the level of regional carbon emissions intensity(Wu et al., 2021)

Energy Consumption Structure (ECS): refers to the share of coal consumption among all kinds of energy consumptions. China's energy structure is mainly based on coal, which makes us highly dependent on high-carbon energy sources. And this kind of energy source plays an important role in our environment pollution (Abbasi et al., 2022).

Industrial structure (IS): refers to what part of the secondary industry's output occupies among all outputs. Fast industrialization has been one of the causes resulting in serious environmental pollution in China (Liu & Bae, 2018; Lu et al., 2026).

Domestic Technological Progress (TCD), measured as the total number of patent approvals. Technological progress may have both direct and indirect effects on carbon emission levels, which is also one of the main elements driving economic development and carbon emissions. Improved technology would help with the local economy developing; but at the same time, if firms adopt new "dirty" technologies for manufacturing purposes, then it will aggravate local environmental issues. Otherwise, should they adopt new clean technologies when producing goods, then carbon emissions will decline (Yang et al., 2021; Li et al., 2024).

The study implements an econometric analysis based on a panel composed of all 30 provinces (regions, municipalities) (except Tibet Autonomous Region, Hong Kong Special Administrative Region, Macau Special Administrative Region, and Taiwan Province, because of some lack of data), during the period of 2012-2020. Among them, energy consumptions such as coal consumption, oil consumption, and gas consumption all refer to regional statistical yearbooks. Carbon emissions are referenced according to CEADs-China (China) Emission Accounting Dataset. Environmental protection investment data mainly comes from provincial government work report and China Environmental Statistics Yearbook. Permanent resident population at year-end, regional GDP, secondary industry output value, number of authorized patent counts, local investment intensity, etc., are derived from provincial/city level statistical yearbooks. Coal conversion factor, crude oil conversion factor, and natural gas conversion factor refer to China Energy Statistical Yearbook. Descriptive statistics about each variable are presented in Table 2. Missing values of some provinces with incomplete data were filled up by taking means of other years' observations to replace the missed ones.

Table 2. Descriptive statistics of variables

Variables	Obs	Mean	Std.Dev	Min	Max
CE	270	0.0269	0.0231	0.0028	0.1283
GB	270	0.0597	0.1187	0.0000	1.0000
ER	270	0.0053	0.0020	0.0016	0.0146
EC	270	86.6521	191.0178	0.0000	1061.51
GDP	270	17790.65	14990.1	896.9	82163.2
POP	270	4482.011	2684.378	554.00	10999
ECS	270	0.0244	0.0103	0.0074	0.0781
IS	270	0.4681	0.0811	0.1926	0.5905
TCD	270	60318.31	91568.78	431	512429
HPI	270	12705.37	9728.095	583.24	53322.94
ECI	270	1.166	0.694	0.370	2.471

4 Results

4.1 Evaluation results of the provincial development level of the green building industry

According to the developed indicator system and calculation approach, we calculated the development levels of 30 provincial regions' green building industries in China, which can be referred to from Figure 1.

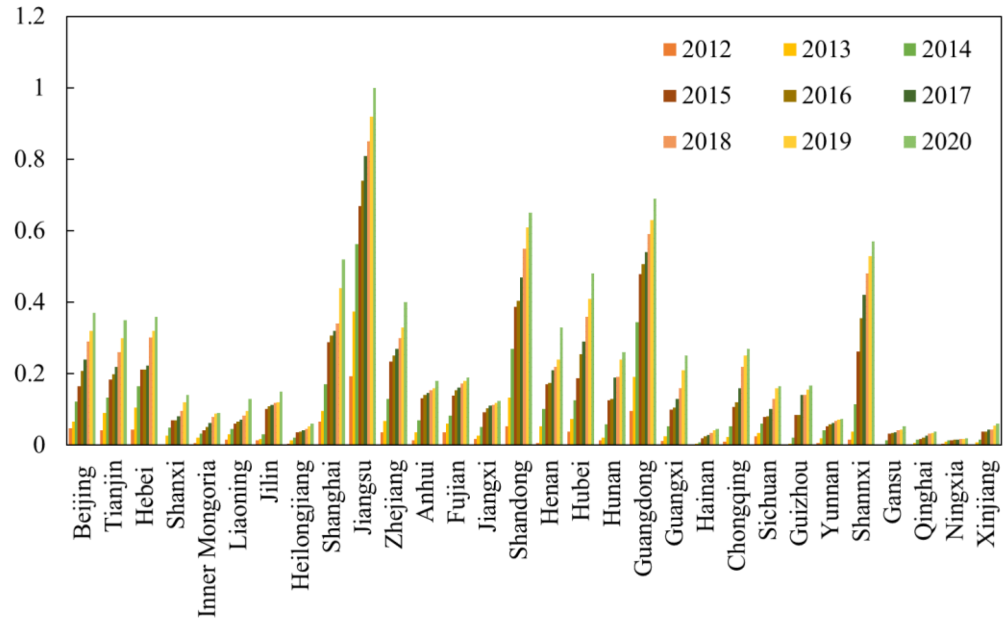


Figure 1: Provincial Development Level of Green Building Industry (2012-2020)

In addition, there exists considerable difference among different regions regarding the development level of green buildings nationwide. Some provinces (cities/autonomous regions), e.g., Jiangsu, Guangdong, Shandong Province, Shaanxi Province, Shanghai, Hubei Province, Zhejiang Province, Beijing Municipality, Tianjin Municipality, Hebei Province, and so forth, have their development levels higher than that of the whole country; while Jiangsu has the highest one among them. In contrast, certain parts, for example, Ningxia Autonomous Region, Qinghai Province, Hainan Province, Gansu Province, Heilongjiang Province, Xinjiang Autonomous Region, Inner Mongolia Autonomous Region, Yunnan Province, Liaoning Province, etc., have achieved relatively low development levels compared to the entire country. Among all these areas, Ningxia has the lowest one.

In terms of growth trends, among all provinces studied, Jiangsu's development in terms of the green building industry was progressing at the best rate; then came Guangdong, Shandong, Shanghai, and Zhejiang. Coastal areas have both a higher development degree and a faster increase rate than other provinces; while Beijing-Tianjin-Hebei region is ahead of other central provinces but still falls behind coastal ones in development level. The western provinces performed worst among them; their developing situation was quite bad, developing slowly as well.

As such, we have found out that the spatial layout of how developed China's green construction industry is also very close to China's economic development gradient from east to west; therefore, there exists an imbalanced situation in which the east performs better than the central and western ones. Hence, this research finding has brought about some fresh understanding about the spatial features of China's green building industry development.

4.2 Carbon reduction effects of green building industry

According to formula (3), we can see its benchmark regression result from Table 3. Among them, in the particular estimation method, column (1) does not contain two kinds of mechanism variables (i.e., ln*HPI* and *ECI*), but column (2) contains those mechanism variables when regressed. Changes in R2 and coefficients of the main explanatory variable GB have already told us about the functions of the above-mentioned two kinds of mechanism variables.

Table 3. Benchmark regression results

	(1)	(2)
GB	-0.2013*** (0.0517)	-0.1930*** (0.0521)
ER	-0.0337** (0.0081)	0.0285** (0.0093)
lnEC	0.0089** (0.0029)	0.0091** (0.0029)
lnGDP	-0.0162*** (0.0011)	-0.0143*** (0.0012)
lnPOP	0.0029 (0.0301)	0.0035 (0.0292)
ECS	1.3166*** (0.0621)	1.3305*** (0.0577)
IS	0.0891** (0.0254)	0.0789** (0.0266)
lnTCD	-1.0311 (0.7273)	-1.0234 (0.7280)
lnHPI		0.8641*** (0.1092)
ECI		0.0972*** (0.0089)
individual fixed effects	✓	✓
time fixed effects	✓	✓
N	270	270
R-sq	0.2640	0.3021

Notes: ***,**,* mean significant at 1%, 5%, 10% level, respectively. Robust standard error (in parenthesis).

The coefficient of *GB* in Column (1) from Table 3 has a significant negative sign, which means that the development of green buildings, to some extent, will decrease regional carbon emissions intensity. At the same time, the coefficient of *ER* among all control variables is significantly negative at the 5% level, which indicates that if we raise our environmental regulation level, we may achieve lower carbon emissions. This point agrees with what previous studies have already shown us. In addition, the coefficient of ln*GDP* also turns out to be significantly negative. That's to say, economic development plays an important part in reducing carbon emissions and proves that China lies somewhere in the middle or late stage of EKC (Environmental Kuznets Curve); therefore, there is a decreasing coupling relationship between economic progress and environmental protection. And we could also put forward such an argument based on these results: Compared with less developed areas, more economically developed areas usually produce fewer CO2 in total. Therefore, it also reveals that there might exist certain spatial inequality among all the regions regarding economic development as well as their respective carbon emissions situation. The coefficient of technology progress is negative, although it is insignificant, probably because the suggested green technologies have not achieved their full potential or some part of them has just been implemented as concrete results. At present, these technology innovations fall short compared with traditional energy-intensive manufacturing industries, which are deeply integrated in China's economy. So, the above index hasn't caused a huge amount of CO2 reduction so far.

Energy endowment (EC), industrial structure (IS), and energy consumption structure (ECS) have all shown very strong positive effects; they will not increase carbon emission intensity. First of all, EC has such strong significance, meaning that quite some resource-endowed cities in China can hardly depart from their previous highly energy-intensive economic growth model, which produces what we call "resource curse." IS also means something – China's secondary industry is still very energy-intensive and highly polluting/carbon emitting. ECS shows one thing here: how much proportion coal accounts for the whole energy mix. Such kind of positive coefficient coincides with our findings in the existing literature, i.e., traditional fossil fuel-based energy consumption is still one of the most important factors causing very heavy amounts of carbon emissions.

As shown in column (2) of Table 3, we add in both of our mechanisms variables, which are as follows: local investment intensity; energy consumption intensity. In comparison to the regression result of column (1), there has been a great increase in R2, proving that adding mechanisms variables improves the explanation ability of our model. And also, these kinds of variables have a very important influence over carbon emission intensity since their own regression coefficients are significant. Besides, notice the change of one core variable GB's regression coefficient, whose absolute value decreases from 0.2013 to 0.1930, implying that once we introduce those mechanisms variables, the negative effect of the development level of the green buildings industry exerted upon carbon emission intensity will weaken correspondingly. So, this kind of phenomenon can prove, indirectly, that how the green buildings industry influences carbon emission intensity might run through these two kinds of mechanisms variables. Hence, if we build an interactive model, we can observe from its coefficients whether the green buildings industry could reduce carbon emission indirectly through those kinds of mechanisms variables, so as to find out some ways through which the green buildings industry achieves emission reduction.

4.3 Mechanisms of carbon reduction effects in green building industry

The green development theory, mentioned above, points out that the green development theory puts emphasis on obtaining higher resource usage efficiency and cleaner means of production when implementing the green industrial transformation. Energy consumption intensity is one key measure of energy use efficiency at the production stage; hence, it can reflect how much carbon emission has been reduced thanks to more intensive and effective use of energy in the green building industry. According to the "pollution haven" hypothesis, high-pollution generating activities have always been favored because they require less capital than those low-polluting ones, which would attract more investments instead. Even though, compared to the conventional building sector, green building industry causes less pollution; however, considering its huge initial cost investment, it is still difficult to gain attention among investors at present. Therefore, investment preference will limit the expansion of the green building industry, thus weakening its role in cutting down carbon emissions. In order to tackle possible multicollinearity problems if we put both interaction terms into the equation together as explanatory variables, we use a stepwise method when doing regressions according to Equation (4). We add interaction terms constructed with the development level of the green building industry and each single mechanism variable separately into the same regression. Mechanism analysis results are presented in Table 4.

Table 4. Mechanism analysis results

	(1)	(2)
GB	-0.3244***	-0.3192***
	(0.0491)	(0.0502)
ER	-0.0279**	0.0275**
	(0.0087)	(0.0088)

lnEC	0.0065*	0.0063*
	(0.0012)	(0.0013)
lnGDP	-0.0193***	-0.0211***
	(0.0034)	(0.0031)
lnPOP	0.0031***	0.0038***
	(0.0001)	(0.0001)
ECS	1.0779***	1.1034***
	(0.0432)	(0.0431)
IS	0.0382*	0.0401*
	(0.0088)	(0.0087)
lnTCD	0.9321	0.8706
	(1.0221)	(1.1321)
lnHPI	0.6921***	0.8593***
	(0.1201)	(0.1093)
ECI	0.0967***	0.0731***
	(0.0093)	(0.0084)
lnHPI×GB	1.0412***	
	(0.0324)	
ECI×GB		-0.9342***
		(0.0419)
individual fixed effects	✓	✓
time fixed effects	✓	✓
N	270	270
R-sq	0.4263	0.4451

Note: ***, **, * denote significance at 1%, 5%, and 10% level, respectively. Robust standard errors in parentheses.

It could be known from Table 4: except for its own main effect variable and mechanisms variable, directions, sizes, and significance levels of coefficients of all kinds of control variables have changed very little. That means our estimation results are very stable. Secondly, comparing with results of regressing in Table 3, we can find out from Table 4 that when adding mechanism variables and interaction terms, their R^2 values increase obviously. Therefore, this also suggests that there indeed exist such channels through which green building industry development impacts on carbon emission intensity indirectly by way of affecting local investment intensity and energy consumption intensity.

(1) Column shows the regression result of mechanism test for local investment intensity; when adding their interaction term into the model, the directions and significances of GB's coefficient and lnHPI's do not change, which implies that both of them still have a direct impact on carbon intensity. Meanwhile, the interaction term's coefficient turns significantly positive here. Such a kind of result needs us to take the partial derivative of GB about lnHPI. Then, its partial derivative form becomes one-variable linear regression mode, whose intercept is just GB's coefficient and slope refers to interaction term's coefficient respectively. Therefore, when lnHPI increases, the negative impact of GB upon carbon reduction will decrease gradually, which means that there exists some crowding-out effects of local investment intensity towards carbon reduction brought about by the development of green buildings industry, implying possible suppression from the development of high-carbon emission industries on both the development and carbon-reducing impacts of the green building industry.

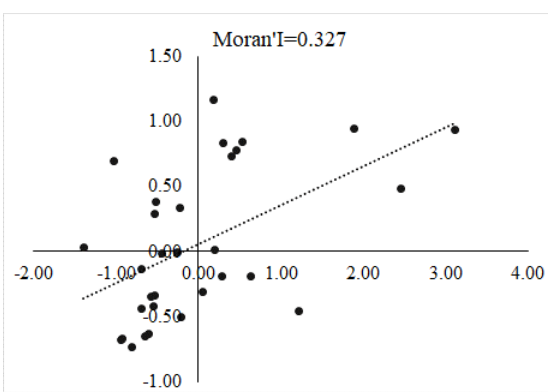
The above is the content of Column (2) of Table 4, which shows the mechanism test result of energy consumption intensity. In order to test if the development of the green building industry can reduce carbon emission intensity by adjusting energy consumption intensity, we use GB here as a mechanism variable. The mechanism effect needs to be differentiated with respect to ECI so as to get a function of one variable which equals to GB. Then, the intercept of this function is our estimated parameter of ECI; while its slope is our estimation parameter of the interaction term. Slope's coefficient has passed significance test at the 1% level, but it is also positive, which means there exists a direct positive relationship between both energy consumption intensity and carbon emission intensity. Interaction term's coefficient is negative (-0.9342) with a significant level <0.01. This tells us: When GB rises, the positive impact of energy consumption intensity on carbon emission intensity will go down evidently. Therefore, we could make such a conclusion: The development of green buildings could alleviate those kinds of increases in carbon emissions which are caused by the rise of energy consumption intensity.

4.4 Identification of spatial correlation between green building industry development and carbon emissions

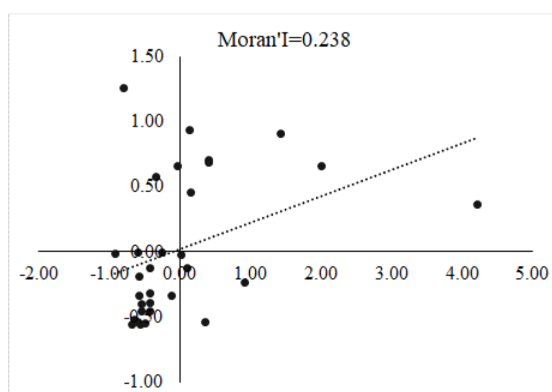
Considering the spatial diffusion characteristics of carbon emissions themselves, numerous studies on carbon emission reduction inevitably discuss spatial spillover effects and have verified the objective existence of such spillovers (e.g., Li and Wang, 2022; Fang et al., 2025). Therefore, relying solely on non-spatial models to identify the emission reduction effects of the green building industry may carry the risk of estimation bias, while also failing to objectively control whether other independent variables exert spatial spillover effects on carbon emission intensity. In this section, we focus on the spatial spillover effects of carbon reduction by the green building industry. Before conducting spatial econometric analysis, we first analyze the spatial characteristics of the development level of the green building industry and carbon emission intensity, followed by a spatial correlation analysis. Only if both variables exhibit significant spatial autocorrelation can we further construct spatial econometric models to examine the pathways and mechanisms of spatial spillovers. Spatial autocorrelation characteristics of the two variables are compared using spatial correlation analysis. The global Moran's I index can reveal whether variables have spatial correlation under a given spatial association pattern (Anselin, 1995). The calculation method is shown in Equation (5):

$$I = \frac{n \sum_i \sum_{i \neq j} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\left(\sum_i \sum_{i \neq j} w_{ij}\right) \sum_i (y_i - \bar{y})^2} \tag{5}$$

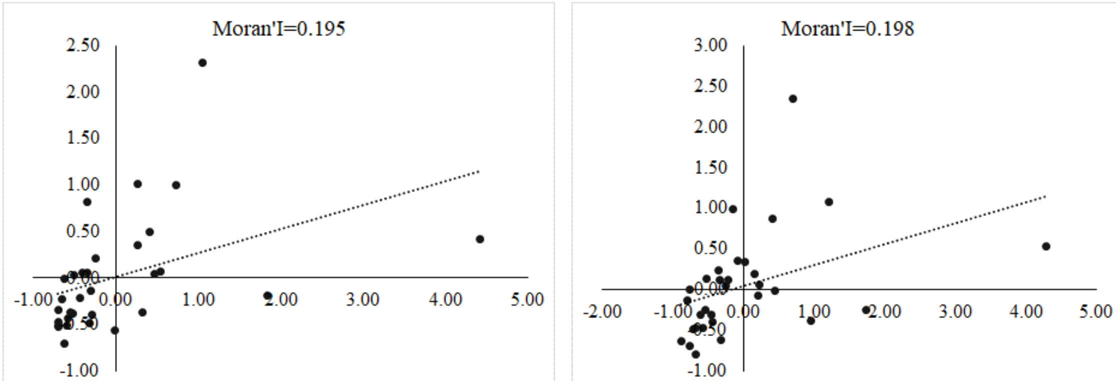
where w_{ij} is the spatial weight. An adjacency matrix is adopted, meaning that adjacent provinces take a value of 1, otherwise 0. This reveals whether carbon emissions and the development level of the green building industry exhibit obvious spatial clustering patterns. Based on data from 2016 and 2020, Moran scatterplots are drawn using the Moran's I index and spatial lag terms.



a. Moran scatterplot of carbon emission intensity (2016)



b. Moran scatterplot of carbon emission intensity (2020)



c. Moran scatterplot of green building industry development level (2016)

d. Moran scatterplot of green building industry development level (2020)

Figure 2. Moran scatterplots of emission intensity and green building industry development level

In the Moran scatterplots of emission intensity and green building industry development level (Figure 2), each dot represents one of China's 30 provincial-level administrative regions. In panels (a) and (b), the horizontal axis represents the carbon emission intensity of each region, and the vertical axis represents the spatially weighted carbon emission intensity value (spatial lag), indicating the degree of spatial lag of carbon emission intensity across regions. In panels (c) and (d), the horizontal axis represents the development level of the green building industry in each region, and the vertical axis represents the spatially weighted development level of the green building industry, indicating the degree of spatial lag of green building industry development. The four quadrants formed by the horizontal and vertical axes have the following meanings: Quadrant I: High-High (H-H) clustering – regions with high carbon emissions/high green building industry development are surrounded by regions with high carbon emissions/high green building industry development. Quadrant II: Low-High (L-H) clustering – regions with low carbon emissions/low green building industry development are adjacent to regions with high carbon emissions/high green building industry development. Quadrant III: Low-Low (L-L) clustering – regions with low carbon emissions/low green building industry development are surrounded by similar low-level regions. Quadrant IV: High-Low (H-L) clustering – regions with low carbon emissions/backward green building industry development are surrounded by regions with high carbon emission intensity/high green building industry development levels.

Panels (a) and (b) of Figure 2 show the Moran scatterplots of carbon emission intensity for 2016 and 2020, respectively. In 2016 and 2020, the number of provinces located in Quadrant I was 8 and 7, respectively; in Quadrant II, 5 and 3; in Quadrant III, 11 and 16; and in Quadrant IV, 6 and 4, respectively. The combined proportion of regions in Quadrants I and III accounted for 63.33% and 76.67% of the national total in 2016 and 2020, indicating that most regions exhibit positive spatial correlation in carbon emission intensity, with neighboring regions having similar carbon emission levels, thus confirming the existence of spatial autocorrelation.

A similar pattern is observed in the development of the green building industry across regions. Panels (c) and (d) of Figure 2 show the Moran scatterplots of green building industry development level for 2016 and 2020. In 2016 and 2020, the number of provinces located in Quadrant I was 8 and 7, respectively; in Quadrant II, 5 and 7; in Quadrant III, 13 and 12; and in Quadrant IV, 4 and 4, respectively. The combined proportion of regions in Quadrants I and III accounted for 70.00% and 63.33% of the national total in 2016 and 2020, indicating that most regions also exhibit positive spatial correlation in green building industry development level, with neighboring regions having similar development levels, again confirming the existence of spatial autocorrelation.

Based on the global spatial autocorrelation analysis results, the development level of China's green building industry and carbon emission intensity exhibit inter-provincial differences, with notable spatial dependence across regions and relatively stable spatial distribution patterns. Both carbon emission intensity and green building industry development level show significant positive spatial autocorrelation, characterized by obvious "high-high" and "low-low" spatial clustering patterns. It is worth noting that over time, the positive spatial autocorrelation of green building industry development level has gradually strengthened, indicating that under the background of green development, neighboring Chinese provinces tend to imitate each other in the green building industry. This reflects the phenomena of "race-to-the-top" and "race-to-the-bottom" among local governments under the decentralized system, as manifested in the green building industry sector. Furthermore, the scatterplot distributions suggest a strong similarity in the spatial clustering patterns of carbon emission intensity and green building industry development level, providing a basis for further research on the spatial spillover effects of green building industry development on carbon emission intensity.

4.5 Analysis of the spatial spillover effects of carbon emission reduction from green building industry development

Commonly used spatial econometric models include the Spatial Lag Model (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM) (Lesage and Pace, 2009). The Spatial Lag Model aims to reduce parameter estimation bias in non-spatial models caused by spatial autocorrelation of the dependent variable, but it ignores the possibility that independent variables may also drive the spatial agglomeration and diffusion of the dependent variable. The Spatial Error Model focuses on the spatial correlation of unobserved error terms, incorporating the spatially correlated part not explained by the dependent and independent variables into the spatial error term; it still primarily seeks to reduce estimation bias under non-spatial models. The Spatial Durbin Model adds the spatial lag terms of independent variables to the Spatial Lag Model, revealing the impact of changes in independent variables in neighboring regions on the dependent variable, and thus helps explain the formation of spatial spillover effects. Therefore, the Spatial Durbin Model not only captures the spatial diffusion pattern of carbon emissions but also reveals the spatial mechanisms through which the spatial spillover characteristics of independent variables affect carbon emissions (Zhou et al., 2023). The model is specified as in Equation (6):

$$CE_{it} = \alpha + \lambda_1 W \times CE_{it} + \lambda_2 GB_{it} + \lambda_3 W \times GB_{it} + \sum \beta_k X_{it,k} + \sum W \times \beta'_k X_{it,k} + \mu_i + \eta_t + \varepsilon_{it} \tag{6}$$

where W is the spatial weight matrix. Three types of spatial weight matrices are employed to examine the pathways and patterns of spatial spillovers of carbon emissions across Chinese provinces: **Adjacency weight matrix**: takes the value 1 if two provinces are adjacent, otherwise 0. **Geographic distance matrix**: the matrix entries are the spherical distances calculated from the longitude and latitude of the provincial capitals of province i and province j. **Economic-geographic matrix**: expressed as $W_E = W_d \cdot diag(\bar{E}_1/\bar{E}, \bar{E}_2/\bar{E}, \cdots, \bar{E}_n/\bar{E})$, where W_d is the spherical distance matrix between provincial capitals, $\bar{E}_i$ is the mean GDP of province i over the study period, and $\bar{E}$ is the national mean GDP over the study period. The economic-geographic matrix implies that when the economic share of province i is larger than that of province j $(\bar{X}_i/\bar{X}) > (\bar{X}_j/\bar{X})$, region i$i$ exerts a stronger economic radiation effect on region jj, but this effect decays with increasing geographic distance. Other variables are defined as before.

Based on the Spatial Durbin Model and the three spatial weight matrices, regression analysis is conducted using the maximum likelihood method (Bivand and Piras, 2015). This study focuses on the spatial spillover effects of the green building industry development level and the mechanism variables. The coefficients of the control variables are discussed elsewhere. The estimation results of the spatial spillover effects among Chinese provinces are shown in Table 5.

Table 5. The estimation results of the spatial spillover effects

	(1)	(2)	(3)
	Adjacency weight	Geographic distance	Economic geographic
GB	-0.0187**	-0.0174**	-0.0159*
lnHPI	0.0189***	0.0170***	0.0233***
ECI	0.0313***	0.0289***	0.0356***
W*GB	-0.0037	-0.0079*	0.0287**
W*lnHPI	0.0106***	0.0092**	0.0278***
W*ECI	0.0635**	0.0512**	0.0973***
W*CE	0.2308***	0.1983***	0.3734***
Controls	✓	✓	✓
W* Controls	✓	✓	✓
individual fixed effects	✓	✓	✓
time fixed effects	✓	✓	✓
R-sq	0.8755	0.9102	0.9398
log-likelihood	956.3785	989.2123	981.7831

Note that ***, **, * denote significance at 1%, 5%, and 10% level respectively.

Column (1) of Table 5 presents the baseline results estimated using the adjacency matrix. The coefficient of the spatial lag term *W*CE* is significantly positive at the 1% level, indicating a clear diffusion phenomenon of carbon emissions across Chinese provinces. The coefficient of green building industry development (*GB*) is significantly negative, suggesting that developing the green building industry brings significant carbon reduction effects to the local region. The coefficient of *W*GB* is negative but not significant, implying that an overall increase in the development level of the green building industry in neighboring regions has not yet significantly reduced local carbon emissions; the spatial spillover effect is not significant. The coefficients of local investment intensity (ln*HPI*) and energy consumption intensity (*ECI*) are both significantly positive, similar to the non-spatial model estimates, which to some extent indicates robustness. The coefficients of *W**ln*HPI* and *W*ECI* are both significantly positive, confirming that increased investment intensifies the spatial diffusion of carbon emissions, and that an overall increase in energy consumption intensity in neighboring provinces implies spatial agglomeration of high-carbon industries, which inevitably leads to spatial agglomeration and diffusion of carbon emissions.

The adjacency weight matrix is simple and easy to handle in model construction but has certain limitations. First, the adjacency matrix assumes that the interaction between regions depends solely on whether they are geographically adjacent, i.e., the spatial spillover effects from neighboring provinces to the local province are spatially homogeneous. This deviates slightly from the objective reality of industrial factor flows and carbon emission diffusion. Second, the adjacency matrix may incorporate multiple complex spatial association patterns, leading to impure estimated coefficients. Therefore, we further investigate the geographic and spatial spillover effects of the green building industry on provincial carbon emission reduction using the geographic distance matrix and the economic-geographic matrix.

Column (2) of Table 5 presents the spatial econometric regression results based on the geographic distance matrix. After accounting for geographic distance, the coefficient of green building industry development (*GB*) remains significantly negative, but the coefficient is -0.0174, which is smaller than the estimate obtained with the adjacency matrix. The spatial lag term of green building industry development level (*W*GB*) is significantly negative at the 10% level, indicating that the development of the green building industry can, to some extent, bring carbon reduction effects to neighboring provinces. From an estimation perspective, this also suggests that the geographic distance matrix better reflects the diffusion pattern of spatial spillover effects of carbon reduction. The coefficients of local investment intensity (ln*HPI*) and energy consumption intensity (*ECI*) are both significantly positive, and their spatial lag terms (*W**ln*HPI* and *W*ECI*) are also significantly positive. However, compared with the adjacency matrix estimates in column (1), the absolute value of the coefficient of *W**ln*HPI* is smaller, indicating that the carbon emission diffusion effect driven by local investment intensity gradually decays with increasing geographic distance, and is therefore smaller than the estimate under the adjacency matrix. The absolute value of the coefficient of W*ECI*W*ECI* under the geographic distance matrix shows a similar pattern compared with the adjacency matrix estimate. This further indicates that in geographic space, these two driving forces tend to push carbon emissions to shift and diffuse to neighboring regions.

Column (3) of Table 5 presents the spatial econometric regression results under the economic-geographic matrix. The direction and significance of the coefficients of green building industry development level (*GB*), local investment intensity (ln*HPI*), and energy consumption intensity (*ECI*) are similar to those obtained with the adjacency matrix and geographic distance matrix, indicating that the model estimates are robust. Regarding the spatial lag term of green building industry development level (*W*GB*), the coefficient is significantly positive at the 5% level. Combined with the significantly negative coefficient of *GB*, this suggests that while the development of the green building industry helps reduce local carbon emissions, it also pushes carbon emissions to shift to economically less developed regions. This is consistent with the carbon emission transfer pattern observed under China's gradient economic development model. Although the directions of the coefficients of the two spatial lag terms *W**ln*HPI* and *W*ECI* remain unchanged, their magnitudes change significantly compared with the estimates under the previous two matrices. The absolute values are significantly larger than those under the adjacency matrix and geographic distance matrix, indicating that an increase in local investment intensity and energy consumption intensity significantly drives carbon emissions to shift to economically less developed regions. The spatial spillover pathway of carbon emissions is more characterized by transfer from economically developed regions to surrounding economically less developed regions, rather than uniform geographic diffusion to neighboring areas. This is highly consistent with the location choice process of high-carbon enterprises.

The regression results and analysis of the Spatial Durbin Model preliminarily reveal the existence of spatial spillover effects. However, because the parameters include feedback effects (i.e., the impact on other regions may in turn affect the original region), parameter estimates may be biased and difficult to interpret. The partial differential decomposition method proposed by Lesage and Pace (2009) decomposes the total effect matrix into direct and indirect effects, thereby avoiding the bias caused by feedback effects on the estimated coefficients. The effect decomposition is shown in Table 6.

Table 6. Direct and indirect effects

	Adjacency weight		Geographic distance		Economic geographic	
	direct effects	indirect effects	direct effects	indirect effects	direct effects	indirect effects
GB	-0.0212**	-0.0066	-0.0248**	-0.0078*	-0.0182**	0.0199**
lnHPI	0.0371***	0.0094**	0.0316***	0.0061*	0.0388***	0.0114***
ECI	0.0419***	0.0430**	0.0412***	0.0475**	0.0429***	0.0651***

Note that ***, **, * denote significance at 1%, 5%, and 10% level respectively.

Table 6 presents the estimation results of the direct and indirect effect decomposition. It can be seen that, although the coefficient magnitudes have changed compared with the estimates in Table 8, the direction of each coefficient has not changed significantly, nor does it affect the conclusions drawn from the above analysis. This indicates that the estimation results of this study are relatively robust. Meanwhile, because the spatial weight matrices for the geographic distance matrix and the economic-geographic matrix are not 0-1 matrices, the feedback effect in the partial differential decomposition is larger than that of the adjacency matrix, leading to somewhat smaller indirect effect estimates. Nevertheless, the results show that under the economic-geographic weight matrix, the indirect effects of local investment intensity (ln*HPI*) and energy consumption intensity (*ECI*) remain higher than those estimated under the adjacency matrix and the geographic distance matrix. This further confirms the spatial pattern whereby carbon emissions tend to shift from economically more developed regions to relatively less developed regions.

4.6 Analysis of spatial spillover mechanisms

The mechanism analysis of the emission reduction effect of green building industry development indicates that the carbon reduction contribution of green building industry development is weakened by an increase in local investment intensity, while green building industry development also reduces carbon emissions by lowering local energy consumption intensity. The spatial econometric analysis reveals that an increase in the development level of the green building industry in a region leads to the transfer of carbon emissions to economically less developed areas. This may be due to the fact that green building industry development drives local investment intensity and energy consumption intensity towards less developed regions, a phenomenon similar to the spatial agglomeration of investment in polluting industries resulting from increased clean investment in a region (Zheng and Shi, 2017). To test this hypothesis, we use ln*HPI* and *ECI* as dependent variables, respectively, and the green building industry development level (*GB*) as the core explanatory variable, and construct Spatial Durbin Models based on the economic-geographic distance matrix to examine whether green building industry development promotes the transfer of local investment intensity and energy consumption intensity to economically less developed regions. The results are shown in Table 7.

Table 7. Analysis of spatial spillover mechanisms (based on the economic-geographic distance matrix)

	(1)	(2)
	Y: lnHPI	Y: ECI
GB	-0.0131	-0.0289*
	(0.0291)	(0.0072)
W*GB	1.4638*	0.0648**
	(0.8728)	(0.0102)
W* Controls	✓	✓
individual fixed effects	✓	✓
time fixed effects	✓	✓
N	270	270

R-sq	0.1921	0.1791

Note that ***, **, * denote significance at 1%, 5%, and 10% level respectively.

In column (1) of Table 7, the coefficient of green building industry development level (*GB*) is not significant, indicating that local green building industry development does not have a significant negative impact on local investment intensity. This may be due to the short development time and small scale of the green building industry. However, the spatial lag term (*W*GB*) is significantly positive at the 10% level, suggesting that the development of the green building industry in neighboring regions to some extent drives investment towards the local region.

In column (2) of Table 7, the coefficient of *GB* is significantly negative, consistent with the previous estimation results, indicating a certain degree of robustness. The spatial lag term (*W*GB*) is significantly positive at the 5% level, indicating that the development of the green building industry in neighboring regions drives energy consumption towards the local region. From the correlation coefficients discussed earlier, there is a strong positive correlation between the development level of the green building industry and environmental regulation. This implies that regions with a higher development level of the green building industry tend to have stricter environmental regulations. This process suggests that, under the pressure of local advocacy for green building industry development, high-carbon enterprises may potentially change their location choices and relocate to economically less developed regions.

The mechanism analysis preliminarily reveals the pathways of spatial spillover effects of carbon emission reduction brought about by the development of the green building industry. First, local investment intensity still favors industries with relatively high carbon emissions, creating a conflict with the development of the green building industry, leading to mutual crowding out. Local advocacy for green building industry development potentially promotes the transfer of local investment intensity to surrounding regions, thereby increasing carbon emission intensity in those surrounding regions. Second, the energy consumption required by the green building industry itself is lower than that of the traditional construction industry. When a region develops the green building industry, local energy demand decreases, and the surplus energy is allocated to surrounding regions. Under China's "core-periphery" spatial economic development pattern, the transfer of energy consumption shifts to surrounding regions, resulting in spatial spillovers of carbon emissions.

4.7 Robustness discussion

The above analysis of the moderating effect has tentatively shown us some aspects of how the growth of the green building industry brings about carbon reductions. But we also need some further examination work to make sure our test of these mechanisms is valid. Regarding the first kind of pathway related to investments, whether there will be such a "crowding-out effect" relies upon one precondition, i.e., whether there exists conflicts between FDI and green building industries. Therefore, when local investment intensity increases, it might squeeze out local green building industry development at the same time. As far as the second type of pathways concerning energy intensity is concerned, if our green building sectors want to affect carbon emissions via influencing energy intensity, then we also have to prove that indeed our green buildings can lower energy intensity, thus reducing carbon emissions.

Therefore, two additional analyses have been made, which can be seen in Table 8.

Table 8. Supplementary tests for mechanism analysis

	(1)	(2)
	Y: GB	Y: ECI
lnHPI	-0.7122*** (0.0039)	
GB		-0.3320** (0.0015)
Controls	✓	✓
individual fixed effects	✓	✓
time fixed effects	✓	✓
N	270	270
R-sq	0.2311	0.1890

Note that ***, **, * denote significance at 1%, 5%, and 10% level respectively. All robust standard errors are in brackets.

In column (1) of Table 5, we can see ln*HPI* as our independent variable, while *GB* is our dependent variable. It means that FDI increases will have negative effects on how developed the green building industry is (*GB*). Hence, this proves that there is a kind of "crowding-out" effect brought by the local investment intensity towards green building industry development. In column (2) of Table 5, we could find that *GB* was used as our independent variable here, and *ECI* acted as our dependent variable. Therefore, it tells us that the development degree of green building industry would reduce energy consumption intensity to some extent. And such result also powerfully demonstrates one of the ways through which green building industry development realizes their carbon emission reduction objective: lowering energy consumption intensity. At the same time, we have re-estimated the results of the Spatial Durbin Model. The coefficient changes are very small, and the direction and significance of the main coefficients show no obvious change. Due to space limitations, these results are not shown here.

5 Conclusions

This study evaluates the development of China's green building industry (GBI) across 30 provincial regions from 2012 to 2020 and systematically investigates how GBI development affects regional carbon emission intensity, through what mechanisms, and with what spatial spillover consequences. The main conclusions are as follows.

First, GBI development significantly reduces regional carbon emission intensity, but spatial imbalance is pronounced. The spatial distribution of GBI development closely mirrors China's economic gradient from east to west, with coastal provinces — led by Jiangsu, Guangdong, and Zhejiang — achieving both higher development levels and faster growth rates than central and western regions. This spatial imbalance means that the aggregate carbon reduction potential of GBI is far from evenly distributed across the country. Macro-structural factors — including energy resource endowment ("resource curse"), industrial structure heavily weighted toward the energy-intensive secondary sector, and high coal dependence in the energy mix — continue to exert significant upward pressure on regional carbon emission intensity, partially counteracting GBI's emission reduction efforts.

Second, GBI reduces carbon emissions through two distinct mechanisms, with opposing implications for policy. The energy efficiency channel operates as expected: GBI development lowers regional energy consumption intensity, which in turn reduces carbon emissions. This confirms the role of technology upgrading and cleaner production within the green building supply chain. However, the investment crowding-out channel works in the opposite direction. Market-oriented investment —

proxied by FDI — exhibits a strong preference for traditional, lower-cost, high-carbon construction activities. As local investment intensity rises, it suppresses GBI's scale of development, weakening its carbon reduction contribution. This finding directly challenges the assumption that market forces alone can drive the green transition in the construction sector.

Third, both carbon emission intensity and GBI development exhibit significant positive spatial autocorrelation, characterized by clear "high-high" and "low-low" clustering patterns. Spatial Durbin Model estimates reveal that, under the geographic distance matrix, GBI development in a region generates modest positive spillovers to neighboring provinces — i.e., it somewhat reduces carbon emissions in nearby areas. However, under the economic-geographic weight matrix, the spatial lag term of GBI development is significantly positive, indicating that GBI advancement in economically developed regions displaces carbon emissions toward economically less developed neighbors. This carbon emission transfer pattern is consistent with the location choice behavior of high-carbon enterprises relocating away from regions with stronger green regulations. Moreover, increases in local investment intensity and energy consumption intensity drive carbon agglomeration and diffusion across provincial borders, with the magnitude of these spillovers being largest under the economic-geographic specification — confirming that carbon emission shifts are structurally embedded in China's gradient economic development model rather than merely reflecting geographic proximity.

Fourth, the spatial mechanism analysis identifies two pathways of spatial spillover. On the investment side, green building development in neighboring regions drives investment intensity toward the local region, as stricter environmental regulation in green-building-advanced areas pushes investment outward. On the energy side, lower local energy demand in GBI-advanced regions redistributes energy consumption to surrounding areas, generating spatial spillovers of carbon emissions under China's "core-periphery" pattern.

In light of these conclusions, we propose the following policy recommendations.

Accelerate GBI development with differentiated regional support. Given the pronounced east–west imbalance in GBI development, a "one-size-fits-all" national policy is insufficient. Central and western provinces should receive tailored fiscal incentives, technical assistance, and capacity-building support to reduce the development gap. Establishing cross-regional GBI cooperation mechanisms — particularly within major city clusters — can help share knowledge, technology, and market experience, and mitigate the risk of emissions being displaced rather than reduced at the national level.

Correct investment biases to unlock GBI's full carbon reduction potential. The evidence that market-oriented investment systematically favors traditional high-carbon construction activities highlights a critical market failure. Governments should strengthen environmental regulations to raise the cost of high-carbon investment, while simultaneously reducing the entry barriers for green building investment through subsidized green finance, tax incentives, and guaranteed procurement. Strengthening R&D investment in green building technologies is particularly important, as cost reduction and performance improvement are essential to making GBI competitive with conventional alternatives without policy support.

Address spatial spillovers through coordinated regional carbon governance. The finding that GBI development in economically advanced regions can transfer carbon emissions to less developed neighbors calls for spatial coordination in carbon management. Regional carbon emission accounting frameworks should incorporate spatial spillover effects rather than treating provinces as isolated units. Policies such as interregional carbon compensation mechanisms, joint environmental regulation enforcement, and coordinated land-use planning can help prevent green development from creating a "pollution haven" effect in peripheral regions.

Integrate energy structure reform with GBI policy. Since coal-dominated energy consumption remains a major driver of carbon emission intensity, GBI's energy efficiency gains are partially offset by the overall high-carbon energy mix. Accelerating the substitution of renewable energy within the construction supply chain — including green building materials manufacturing, on-site energy use, and building operations — is necessary to amplify GBI's carbon reduction effect. Local governments should coordinate GBI development planning with regional energy transition strategies to maximize co-benefits.

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