energies

MDPI

Article

The Impact of Green Innovation on Carbon Emissions: Evidence from the Construction Sector in China

Xinping Li [1], Qiongxia Qin [1] and Yongliang Yang [1,2,3,*]

1 School of Economics and Management, Zhejiang Sci-Tech University, Hangzhou 310018, China; 202120905099@mails.zstu.edu.cn (X.L.); jttqqx@163.com (Q.Q.)
2 Silk and Fashion Culture Research Center of Zhejiang Province, Zhejiang Sci-Tech University, Hangzhou 310018, China
3 Green and Low-Carbon Technology and Industrialization of Modern Logistics, Zhejiang Engineering Research Center, Wenzhou 325100, China
* Correspondence: royyang@zju.edu.cn; Tel.: +86-187-6818-9867

Abstract: Green innovation has been identified as a viable strategy to mitigate the tension between industrial change and pollutant emissions. Relevant research should focus more on the impact of eco-friendly innovations on carbon emissions. Consequently, using a panel data set that covers 30 Chinese provinces from 2005 to 2020, we examine whether there is a carbon-abatement effect of green innovation in the construction sector. According to the findings of a two-way fixed-effects model, green innovation substantially positively influences reduction in dioxide emissions in the Chinese construction industry. The results of a panel threshold model show a significant non-linear relationship between green innovation and carbon emissions when the environmental regulation intensity is used as the threshold variable. Furthermore, we discovered that green innovation cuts carbon emissions considerably through environmental regulation. Finally, the impact of abatement varies significantly between regions, innovation elements, and types of development.

Keywords: green innovation; the construction industry; carbon reduction; threshold effect

check for updates

Citation: Li, X.; Qin, Q.; Yang, Y. The Impact of Green Innovation on Carbon Emissions: Evidence from the Construction Sector in China. *Energies* **2023**, *16*, 4529. https://doi.org/10.3390/en16114529

Academic Editor: Luigi Aldieri

Received: 1 April 2023
Revised: 31 May 2023
Accepted: 3 June 2023
Published: 5 June 2023

1. Introduction

Global warming has been a major study issue worldwide [1], and carbon emissions have considerably contributed to climate change [2]. According to the Sixth IPCC Assessment Report, global warming is anticipated to approach or surpass 1.5 °C in the next 20 years, based on projections of average temperature increases. Carbon emissions have recovered primarily to pre-Newcastle pneumonia epidemic levels, reversing the temporary drop caused by the pandemic in 2020, according to BP's World Energy Statistics Yearbook (2022). This growth is primarily driven by emerging economies, with China accounting for 76.9% of the increase. As a result, China's environmental regulations face the complex and urgent challenge of reducing CO_2 emissions. Achieving China's goal of a sustainable low-carbon economy is contingent on cutting carbon dioxide emissions [3,4].

In response to local and United Nations climate-discussion criticism, the Chinese government is reducing its carbon dioxide emissions. It has committed to cutting carbon emissions in a variety of bold ways. For instance, within the framework of the Paris Agreement, China pledged to achieve carbon peaking by 2030 and carbon neutrality by 2060. As the world's largest developing nation, China will swiftly transition from carbon peaking to carbon neutrality and become a world leader in carbon abatement.

It is crucial to determine the binding influence of technological progress on carbon dioxide emissions in the construction sector [5]. As a major pillar sector in the country's growing urbanization, the construction industry has contributed tremendously to the nation's economic growth. However, there are issues of excessive energy use and emissions [6].

The building industry accounts for around 40% of worldwide carbon emissions. The Chinese construction industry is the largest in the world. According to the China Building Energy Consumption and Carbon Emissions Study (2022), the total energy consumption of the entire building process in 2020 was 2.27 billion tons, accounting for 45.5% of the country's total energy consumption; the total carbon emissions of the building process as a whole in 2020 was 5.08 billion tons of carbon dioxide, accounting for 50.9% of the country's carbon emissions. Using toxic fuels, primary energy consumption, and antiquated technology have increased hazardous emissions and environmental damage [7], resulting in severe emission problems [8]. However, as in all other industries, when new technologies and equipment are generated and put into the construction process, high-value-added, low-energy-consuming products are produced. Energy consumption is more efficient, and construction costs are reduced with lower carbon emissions [9]. New technology-based tools and equipment imply the development of technological innovations [10–12]. As a result, green innovation is a viable path for the construction industry to realize energy-saving and low-carbon development [13]. This has a positive impact on economic, social, and ecological benefits.

Scholars have researched whether green innovation can cut carbon emissions extensively, but a consensus has yet to be reached. Most academics believe that green innovation may reduce carbon emissions while improving environmental quality [14,15]. According to empirical research, green innovation is an effective strategy for achieving a "win-win" situation with respect to high-quality economic growth and environmental conservation [16]. The correlation between green innovation and carbon abatement has also been demonstrated [17,18]. For instance, Du et al. (2019) [19] found that a single threshold effect regulated the impact of environmental innovation on the performance of carbon dioxide emissions. Conversely, other researchers contend that green technology cannot reduce emissions [20–22]. According to Weina et al. (2016) [23], Italy's green innovations may have enhanced environmental output but have not appreciably reduced carbon emissions.

Furthermore, the correlation between green technologies and greenhouse-gas emissions must be better studied, especially in developing countries [24,25]. Other studies have found a trend of increasing carbon pollution across economies, particularly in developing countries undergoing rapid economic growth and industrialization [26,27]. The effect of green technology on CO_2 reduction has been found to differ dramatically between economies [28]. For instance, Dauda et al. (2019) [29] found that innovation has reduced CO_2 emissions in the G6 while increasing them in the Middle East, North Africa, and the BRICS. Chen et al. (2020) [30] found that technological innovation in high-income, high-tech, and high-CO_2-emitting countries can significantly reduce emissions in neighboring countries, while R&D intensity in other countries can even increase CO_2 emissions. Many European countries are also facing economic transformation [31]. It should be mentioned that analogous research relies on a worldwide sample and does not include China. Nevertheless, research in this area is necessary for adopting and improving decarbonization measures in the world's largest rising economy.

The bulk of studies have concentrated on the effect of environmentally friendly innovation on environmental quality. Consequently, further research is necessary to directly demonstrate the carbon-abatement benefits of green technology innovations in the construction industry. Numerous studies have investigated the factors that influence CO_2 emissions in the building sector. However, most of the literature focuses on energy consumption [32], urbanization [33], economic growth [34], environmental regulation [35,36], and carbon rights [37]. Fewer studies consider green innovation as a central explanatory factor. Most domestic and international experts and scholars [6,8] have concluded that technological innovation and industrial carbon emissions are closely linked through different empirical studies. Green technologies are critical to attaining sustainable development goals while having the least detrimental impact on the natural environment [38–41].

Based on current research, we pose two questions: (1) Can green innovation cut carbon emissions effectively? (2) Does green innovation have a non-linear or linear relationship with dioxide emissions? To address the above topics, using panel data from 30 provinces, the impact of green innovation on CO_2 emissions in the construction sector between 2005 and 2020 is empirically explored. The results of green innovations above and below the threshold are validated using a two-way fixed-effects model followed by a double-threshold model. This study establishes a link between carbon dioxide emissions and ecologically friendly innovation. According to the two-way fixed-effects model findings, green innovation has a substantial positive influence on CO_2 emissions reduction in the Chinese construction industry. The panel threshold-effects model results suggest a double threshold effect of green innovation and carbon emissions when the intensity of environmental regulation is used as the threshold variable. Furthermore, we discovered that green innovation cuts carbon emissions considerably through environmental regulation. Finally, the abatement impact varies significantly between regions, innovation elements, and types of development. Although this article found a significant impact of green technology innovation on the total carbon emissions reduction in the construction industry, we did not reach a significant conclusion regarding the proportion of emissions reduction. This could guide regions in China to realize the carbon-reduction effects of green innovation.

The following are four major contributions: First, using a unified statistical analysis method, we investigate the correlations between carbon dioxide emissions and green innovation, both linearly and non-linearly. The global effect of environmentally friendly innovation on environmental quality, notably carbon emissions, is questionable. In this paper, we study the influence of green innovation on CO_2 emissions using a two-way fixed-effects model followed by a double-threshold model. Environmental regulations are included in the study framework for the role of green technology in reducing carbon dioxide emissions. This may contribute to the advancement of research in linked domains. Second, this essay expands the study of green innovation in carbon emissions based on statistics from the Chinese construction sector. We aim to determine whether green technologies provide the building sector with viable ways to combat climate change. A comprehensive evaluation of the role of green innovation in abating emissions in China's construction sector facilitates the creation of decarbonization strategies. In addition, it may serve as a guide for other developing nations as they transition to low-carbon economies. We have discovered a probable mechanism. Numerous studies have yet to examine the indirect impact mechanisms of green innovation in reducing CO_2 emissions in the construction industry. Using a mediation-effect model based on environmental regulation, the mechanism of influence of green innovation on dioxide emissions is examined. Finally, we investigate the varying effects of green innovation on CO_2 emissions in different regions, innovation variables, and province types. Due to the potential diversity of green innovation and dioxide emissions in the building sector, only some studies have assessed whether the spatial relationship varies. This facilitates the formulation of green development plans tailored to local circumstances.

The remaining sections of the paper are organized as follows. Section 2 describes the theoretical analysis and research hypotheses. Technical and research data are presented in Section 3. Section 4 shows the estimated benchmark regression findings, the mediation effect, and heterogeneity analysis results. The results of the study are discussed further in Section 5. The Section 6 summarizes the findings and provides policy suggestions.

2. Theoretical Analysis and Basic Assumptions

2.1. Green Innovation and Carbon Emissions

According to modern economic growth theory, technological progress is one of the major factors in economic growth. Innovation is a requirement for technology development which can reduce the harmful effects of economic growth on the environment [42]. The research and application of green innovations can drive technological progress and industrial transformation, thereby achieving the goal of reducing carbon emissions. This has been well documented internationally. For example, the United Nations Framework Convention on Climate Change (UNFCCC) has embraced "green technology transfer" as a key tool in the fight against climate change. Specifically, green innovations in energy, transport, and buildings can significantly curtail CO_2 emissions by improving energy efficiency and promoting new energy sources.

The relationship between green innovation and CO_2 emissions will vary between the initial and subsequent phases. At the initial stage, green innovation has a relatively small effect on CO_2 emissions abatement. This is because it takes time for a new technology or product to become widespread and diffused. In the subsequent stages, however, the effect of CO_2 emissions abatement will gradually increase as green innovation is widely used and its market share increases. The diffusion of green innovations should therefore be a long-term and gradual process. Innovations and technological developments may result in hazardous waste [43] but may also pave the way for eco-friendly technologies with lighter emission rates. Thus, the relationship can be either positive or negative.

There may be a complex non-linear relationship between green innovation and carbon abatement, with the intensity of environmental regulation being a significant threshold variable. Innovation asymmetry theory suggests that the degree of environmental regulation can create innovation differentiation in the marketplace. When environmental regulations are less stringent, firms may adopt more traditional technologies and experiences to meet environmental requirements. Only adopting more advanced and cutting-edge technologies and innovative solutions can give firms a comparative advantage in the competitive marketplace when the environmental regulation intensity increases. This advantage is more difficult to replicate. Therefore, the higher the environmental regulation intensity, the greater the differentiation of the innovation. The following research hypotheses were generated based on the above analysis:

Hypothesis 1. *Green innovation can significantly reduce carbon emissions in the construction industry.*

Hypothesis 2. *There is a non-linear relationship between green innovation and carbon reduction.*

2.2. The Mediating Role of Environmental Regulation

Innovation theory suggests that firms tend to invest more in eco-friendly technological innovations under the influence of environmental regulatory intensity. When environmental policies and regulations are strengthened, the cost to companies of implementing carbon reductions and reducing their environmental impact increases. As a result, companies tend to adopt more optimal and cost-effective methods to reduce carbon emissions through innovation. Through extensive and in-depth research into environmental regulatory oversight, scholars have found that it can significantly affect technological innovation [44]. The higher the environmental regulation intensity, the tighter the environmental constraints on companies. Companies will have to face stricter emissions standards and environmental responsibilities, which will lead to innovations in technology and processes to improve energy efficiency and cut CO_2 emissions.

The "Porter Hypothesis" posits that environmental regulation may force firms to innovate and enhance their competitive advantage in the marketplace [45]. Adequate environmental regulation has a significant impact on green innovation. In a competitive market environment, firms transform elements of environmental regulation into regional factors of green innovation, enhancing the disincentives to waste emissions. According to the Porter Hypothesis, the relationship between environmental regulation, eco-friendly technologies, and environmental pollution has been explained more scientifically and clearly. In addition, studies have revealed an inverted U-shaped relationship between environmental regulation and environmental pollution [46]. Therefore, environmental regulation plays a mediating role when studying the CO_2 abatement effects of technological innovation. Therefore, we propose the following research hypothesis:

Hypothesis 3. *Green innovation reduces carbon emissions by promoting the intensity of environmental regulation.*

3. Materials and Methods

3.1. Model Specification

3.1.1. Carbon-Emissions Measurement

Numerous research studies have investigated the quantification of CO_2 emissions from the building industry. Generally, these studies can be categorized into three groups: the IPCC approach, the input–output analysis technique, and the life-cycle assessment method. First, carbon emissions are evaluated using energy consumption and carbon dioxide emission factors [47,48]. Furthermore, carbon emissions are estimated by assembling input–output tables and building related mathematical models describing the link between initial input, intermediate input, intermediate output, total input and total output, and final output for each economic system sector [49]. Finally, bottom-up emissions of a product or process are evaluated throughout its life cycle by circling carbon emissions, accounting limits, and collecting carbon emissions data [50,51]. In recent years, the amount of academic research using IPCC methods to study the carbon emissions from the building sector has increased significantly. The primary reasons include the IPCC method's more flexible data selection, straightforward accounting methods, and more reliable computation outcomes. Consequently, the IPCC approach was adopted to estimate carbon emissions in this article.

Based on the CEADS database and regarding Shan et al. (2016) [52], following the IPCC approach, the province-specific dioxide emissions from the energy used by the building sector were calculated.

$$CE_{ij} = AD_{ij} \times NCV_i \times CC_i \times O_{ij} \tag{1}$$

where CE_{ij} are the CO_2 emissions from burning fossil fuel i in the sector j; AD_{ij} represents the fossil-fuel usage for the particular fossil-fuel type and industry; NCV_i is the net calorific value generated per physical unit of fossil-fuel burning; CC_i (carbon content) is the dioxide emissions per net calorific value produced by fossil fuel i; and O_{ij} is the oxidation rate, which is the oxidation ratio during the burning of fossil fuels.

3.1.2. STIRPAT Model

The IPAT model was originally proposed by Ehrlich and Holdren (1971) [53] and extended into the STIRPAT model by Dietz and Rosa (2003) [54]. The model can explain or evaluate the different influences, sources, and magnitudes of environmental stress. The IPAT model can be written as $I = PAT$, where I, P, A, and T denote environmental impact, population, wealth per capita, and technology, respectively.

$$I_i = aP_i^b \times A_i^c \times T_i^d \times e_i \tag{2}$$

where a is a constant term; b, c, and d are the elastic coefficients of the three variables P, A, and T, respectively; and e is an error term and represents random variables, indicating uncontrollable or unobservable random variables. The model can be taken logarithmically on both sides and transformed into a linear equation.

We can use the STIRPAT model [55,56] to understand the main factors that influence carbon emissions from buildings.

$$CE_{it} = \alpha P_{it}^{\beta_1} \times A_{it}^{\beta_2} \times T_{it}^{\beta_3} \times e^{\mu_{it}} \tag{3}$$

where α and β are model parameters and μ is a random disturbance parameter.

In the STIRPAT model, both the coefficients can be estimated as parameters and the effects can be appropriately decomposed [57].

The factors affecting carbon emissions are not only population increase, economic growth, and technological progress. Explanatory variables, core explanatory variables, and control variables can be added to the model above.

3.1.3. Two-Way Fixed-Effects Model

The following regression equation was developed to test the CO_2 abatement effect of green innovation in the construction sector. To control for time and area effects, a two-way fixed-effects model was chosen in this paper.

$$CE_{it} = \beta_0 + \beta_1 Tech_{it} + \beta_2 X_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (4)$$

where i and t, respectively, represent the province and year; CE_{it} denotes the dioxide emissions from the building sector in the province i in period t; $Tech_{it}$ is the number of patents for green inventions in the province i in the period t, denoting the level of green innovation; X_{it} is a collection of factors that impact carbon dioxide emissions; α_i denotes the province fixed effects, controlling for all province-level factors that do not vary over the region; γ_t denotes the year fixed effects, controlling for time-level factors that do not vary by time; and ε_{it} is the residual term. In the above equation, β_1 is this paper's estimated coefficient of interest. If negative and significant, β_1 indicates that green innovation may significantly cut CO_2 emissions from the inter-provincial construction sector.

3.1.4. Panel Threshold Model

The economic rationale for the non-linear impact may be that while an area is in its early phases of development, its major development aim is economic expansion. Currently, technical advancement is more likely to enhance production. Although it has a slight damping impact on carbon emissions [58], the outcome is mediocre. When an area achieves a certain degree of economic development and prioritizes green and sustainable development, technological innovation becomes more focused on green technological innovation, as green innovation supports economic development and improves environmental quality and CO_2 abatement intensity. This study employed the Hansen threshold model [59] to investigate whether there is a non-linear link between green innovation and carbon dioxide emissions. As a threshold variable, we used the intensity of environmental regulation. The single-threshold panel model presented in this study is described below.

$$CE_{it} = \beta_0 + \beta_1 Tech_{it} \times I(Envr_{it} \le \theta) + \beta_2 Tech_{it} \times I(Envr_{it} > \theta) + \beta_3 X_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (5)$$

We extended the single-threshold model to a multi-threshold model, considering the possibility of multiple thresholds.

$$\begin{aligned} CE_{it} = \beta_0 + \quad & \beta_1 Tech_{it} \times I(Envr_{it} \le \theta_1) + \beta_2 Tech_{it} \times I(\theta_1 < Envr_{it} \le \theta_2) + \cdots \\ & + \beta_n Tech_{it} \times I(\theta_{n-1} < Envr_{it} \le \theta_n) \\ & + \beta_{n+1} Tech_{it} \times I(Envr_{it} > \theta_n) + \beta_{n+2} X_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \end{aligned} \quad (6)$$

where $Envr_{it}$ represents the severity of environmental regulation and serves as the threshold variable in year t and province i; θ is the specific threshold value, when $Envr_{it} \le \theta$, $I(\cdot) = 0$ and when $Envr_{it} > \theta$,$I(\cdot) = 1$; and $I(\cdot)$ is an indicator function whose value relies on the link between the threshold variable ($Envr_{it}$) and the threshold value (θ). In model (6), $Tech_{it}$ is the explanatory variable affected by $Envr_{it}$ and β_1~β_{n+1} are the coefficients of the effect of $Tech_{it}$ on CE_{it} when $Envr_{it}$ is in different intervals.

3.2. Variable Definitions

3.2.1. Explained Variable

This study used the construction industry's carbon emissions (CEs) as the explanatory variable. Due to the non-uniformity of physical energy categories consumed in different provinces, all energy consumed in each province was selected for data completeness, excluding energy sources outside the CEADS emission factor table. Secondary energy sources, such as electricity and heat, were omitted to avoid double-counting electricity and heat emissions. This article focuses on absolute carbon reduction, so continuous total data were used. We also tried to use the logarithmic of carbon reduction for the robustness tests, and although doing so is controversial, the results are robust.

3.2.2. Core Explanatory Variable

Green innovation (*Tech*) [60] was taken as the fundamental explanatory variable. Three variables can be used to quantify green innovation: patents, R&D expenditure, and total factor productivity. These metrics indicate the innovation's inputs, outputs, and performance. Patents are a reasonably accurate predictor of environmental innovation [61]. Therefore, the number of patents for green innovation was utilized as a measuring stick. This article focuses on the impact of increasing the number of green patents on carbon reduction, that is, how much carbon emissions can be reduced by adding a green patent.

3.2.3. Threshold Variable and Mechanism Variable

Environmental regulation intensity (*Envr*/*lnEnvr*) was used as both a threshold and a mechanism variable. Existing research needs to have defined criteria for quantifying the rigorousness of environmental regulation, which is a policy variable. Some scholars [62] utilize the ratio of regional GDP to regional total energy consumption as a measurement. The bigger the ratio, the more pronounced the environmental regulation's effect on energy conservation and emissions abatement at a given GDP level. Therefore, we used the ratio of GDP to energy consumption in the construction sector for measurement.

3.2.4. Control Variables

Complex variables influence carbon emissions in the building business. To control the potential impact of other factors and mitigate the endogenous problems caused by omitted variable bias, with reference to the established literature, construction GDP (*lnCongdp*), the number of employees in the construction industry (*lnConjo*) [11], the level of urbanization (*Town*) [63], the degree of openness to the outside world (*Open*) [64], the R&D intensity (*Rede*) [65], the industrial structure (*Indus*) [66], the economic development level (*Pgdp*) [2], and the efficiency of science and technology innovation (*Pate*/*Scit*/*Expe*/*Budge*) [67] were selected as control variables. Table 1 contains a listing of all factors considered for this study.

Table 1. Variable Definitions.

Variable	Name	Variable Measure	Data Sources
	Dependent variable		
CE	Carbon emissions from construction [48]	IPCC	A
	Independent variable		
Tech	Green innovation [60]	Number of patents for green inventions	B
	Threshold variable		
Envr	Environmental regulation intensity [62]	Construction GDP/energy consumption	C and A
	Mediating variable		
lnEnvr	Environmental regulation intensity [62]	Ln (construction GDP/energy consumption)	C and A
	Control variables		
lnCongdp	Construction GDP	Ln (construction GDP)	C
lnConjo	Number of people employed in the construction industry [11]	Ln (number of employees in construction companies)	C
Town	Urbanization level [63]	Urbanization rate	D
Open	Degree of openness to the outside world [64]	FDI/total GDP	D
Rede	R&D intensity [65]	R&D expenditure of industrial enterprises/total GDP	D
Indus	Industrial structure [66]	Construction GDP/total GDP	D
Pgdp	Economic development level [2]	Ln (per capita GDP)	D
Pate	STI efficiency [67]	General budget expenditure	D
Scit	STI efficiency [67]	Domestic patent applications granted	D

Table 1. *Cont.*

Variable	Name	Variable Measure	Data Sources
Expe	STI efficiency [67]	Science and technology	D
Budge	STI efficiency [67]	Science and technology expenditure/general public budget expenditure	D

Notes: In the data sources column, "A" indicates the China Energy Statistical Yearbook, the China Environmental Statistical Yearbook, and the CEADS database; "B" indicates the China Research Data Service Platform (CNRDS) and the statistical reports of the State Intellectual Property Office; "C" indicates the China Statistical Yearbook of the Construction Industry; "D" indicates the China Statistical Yearbook.

Due to the unavailability and scarcity of data, four regions—Tibet, Hong Kong, Macau, and Taiwan—were excluded from this paper. The data from the final panel for thirty Chinese provinces from 2005 to 2020 were selected and interpolated to fill in the missing data for specific provinces. Descriptive statistics for all variables are presented in Table 2.

Table 2. Descriptive Statistics of Variables.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
CE	480	802.149	765.214	13.008	4059.920
Tech	480	725.144	1303.389	0	10,010
Envr	480	18.197	43.817	2.209	489.816
lnEnvr	480	2361.909	819.364	792.690	6194.031
lnCongdp	480	6.774	0.924	3.954	8.784
lnConjo	480	13.640	1.117	10.912	15.962
Town	480	0.552	0.140	0.269	0.896
Open	480	0.022	0.018	0.000	0.082
Rede	480	94.037	52.366	5.833	231.865
lndus	480	0.071	0.023	0.019	0.147
Pgdp	480	10.501	0.658	8.528	12.013
Budg	480	3666.702	2926.775	0.201	17,430.790
Pate	480	41,179.920	75,230.880	79	709,725
Scit	480	90.485	137.640	0.48	1168.793
Expe	480	5055.355	33,142.230	2.237	72.019

Notes: "Std. Dev." denotes the standard deviation.

4. Results

4.1. Two-Way Fixed-Effects Regression Analysis

To test the CO_2 abatement effect of green innovation in the building industry, a two-way fixed-effects model was used as the baseline regression model. In addition, in order to see more clearly whether other factors also influenced the two, we divided the regression model into one that did not include control variables and one that did. To strengthen the credibility of the two-way fixed-effects model, we present the regression results with bootstrap standard errors and control for province–year interaction fixed effects in Table 3. The regression results are shown in Table 3. Column (1) does not contain control variables, column (2) displays results for fixed effects with conventional robust standard errors, column (3) displays regression results with bootstrap standard errors, and column (4) displays regression results controlling for province–year interaction fixed effects. The carbon-reduction effect of green innovation is significant, regardless of the total or proportion of carbon emissions (Appendix B).

The regression coefficients for *Tech* are 0.024, −0.184, and −0.184, as shown in columns (1) and (3), with columns (2) and (3) passing the 1%-significance-level test. For example, column (1) illustrates that the green-innovation regression coefficient is positive and insignificant before including control variables. Upon addition of the control variables, the estimated coefficient of *Tech* is −0.184, which is statistically significant at the 1% level. This indicates that additional variables obscure the results of the baseline regression. According to the regression findings in column (2), a rise in green innovation decreases dioxide emissions in the construction sector across all provinces. From the results for the control variables, the coefficient of *Open* is significantly negative, indicating that the degree of openness to the outside world contributes to the reduction in carbon emissions in the construction industry. Due to economic globalization, trade between countries has become more frequent. The introduction of advanced foreign experience and technology in environmental protection, increased awareness of environmental protection, and increased demand for high quality of life have reduced carbon emissions in the industry.

Table 3. Results of the Two-Way Fixed-Effects Regression Analysis.

	Dependent Variable: CE			
	(1) **FE**	**(2)** **FE_r**	**(3)** **FE_bootstrap**	**(4)** **FE_dt**
Tech	0.024	−0.184 **	−0.184 ***	−0.076 *
	(0.083)	(0.073)	(0.049)	(0.046)
lnCongdp		387.472	387.472	292.618 *
		(377.136)	(251.326)	(163.222)
lnConjo		−35.282	−35.282	89.532
		(216.077)	(97.173)	(73.198)
Town		493.041	493.041	1140.732
		(1832.267)	(1151.909)	(1480.447)
Open		−6933.200 **	−6933.200 ***	−2984.050 **
		(3112.535)	(1741.324)	(1318.868)
Rede		−0.790	−0.790	0.832
		(3.663)	(1.838)	(1.165)
lndus		−5426.363	−5426.363 *	333.546
		(4097.149)	(3141.189)	(1868.609)
Pgdp		−78.562	−78.562	184.983
		(462.698)	(288.796)	(181.879)
Pate		−0.000	−0.000	−0.002 **
		(0.001)	(0.001)	(0.001)
Scit		1.123	1.123	−1.318 **
		(1.321)	(0.794)	(0.519)
Expe		0.002	0.002 **	0.000
		(0.002)	(0.001)	(0.001)
Budge		0.134	0.134 ***	−0.024
		(0.123)	(0.046)	(0.046)
Constant	454 ***	−251	−251	−4672 ***
	(88)	(4837)	(2262)	(1739)
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
R^2	0.231	0.354	0.354	
N	480	480	480	480

Notes: (1) Robust standard errors are in parentheses; (2) "***", "**", and "*" denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.2. Panel Threshold Regression Analysis

According to model (6), whether the threshold-effect test is passed or failed determines whether the panel threshold model can be further manipulated. This threshold effect tests for a non-linear association between the variables. There may be a lagging effect on the impact of *Tech* on *CE*. The model was re-estimated using *Tech*'s first-order lag term for accounting for endogeneity and for validating the non-linear relationship further. Based on Hansen's hypothesis, the threshold-effect test for *Tech* and the first-order lag term of *Tech* were used. Repeating the sample 300 times, the bootstrap technique determined the asymptotic distribution of F-values and the accompanying *p*-values and critical values. The results of the threshold tests indicated that single and double thresholds passed the hypothesis test at the 1% significance level (Table 4). In contrast, the three-threshold effect was insignificant, so the two-threshold model was chosen for analysis.

Table 4. Threshold-Effects Tests for the Existence.

Independent Variable	Number of Thresholds	Threshold Value	F-Statistics	*p*-Value	BS Times	95% Confidence Interval
Tech	Single threshold	4.381	132.11 ***	0.000	300	[4.261, 4.413]
Tech	Double threshold	7.658	75.60 ***	0.000	300	[7.624, 7.671]
Tech	Three-fold threshold	3.499	43.41	0.700	300	[3.461, 4.447]
L.Tech	Single threshold	3.917	103.96 ***	0.000	300	[3.671, 3.921]
L.Tech	Double threshold	7.658	53.10 **	0.020	300	[7.643, 7.671]
L.Tech	Three-fold threshold	3.549	53.47	0.603	300	[3.501, 3.606]

Notes: "***" and "**" denote statistical significance at the 1% and 5% levels, respectively.

According to Table 4, the F-statistic is statistically significant at the level of significance of 1% in the double-threshold model. There are two thresholds, with *Tech* thresholds of 4.381 and 7.658 and *L.Tech* thresholds of 3.917 and 7.658, respectively. Figures 1 and 2 show the likelihood statistics. As shown, the above threshold values are valid.

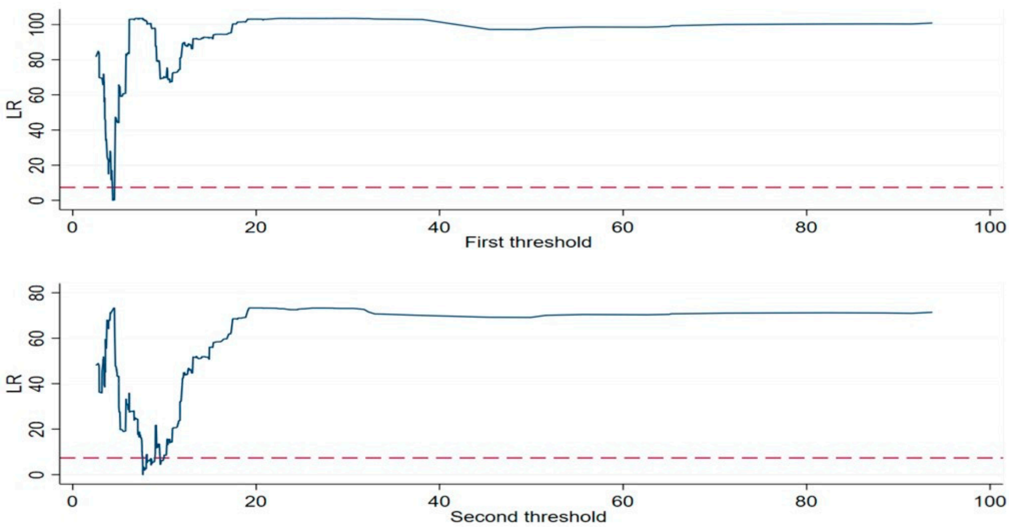

Figure 1. Threshold Likelihood Statistics of *Tech*.

Based on the threshold test, we chose environmental regulation as the threshold variable and performed a two-threshold-model regression analysis. In column (1) of Table 5, the results for *Tech* are displayed. When *Envr* is below the threshold value of 4.381, the regression coefficient of *Tech* on *CE* is 1.025, and the result is significantly positive; when *Envr* is between the threshold value of 4.381 and 7.658, the coefficient of *Tech* is 0.194, and the result is significantly positive; when *Envr* is above the threshold value of 7.658, the coefficient of *Tech* is −0.152, and the effect is significantly negative. This shows that when environmental regulations are weak, green innovation has a negligible influence on CO_2 abatement in the construction sector. However, as environmental regulation grows more stringent, the coefficient of *Tech* decreases. Eventually, it becomes negative and plays a larger role in lowering CO_2 emissions. In addition, the same outcomes are realized (see column (2) of Table 5). Therefore, the double-threshold model results suggest a non-linear relationship between green innovation and CO_2 emissions.

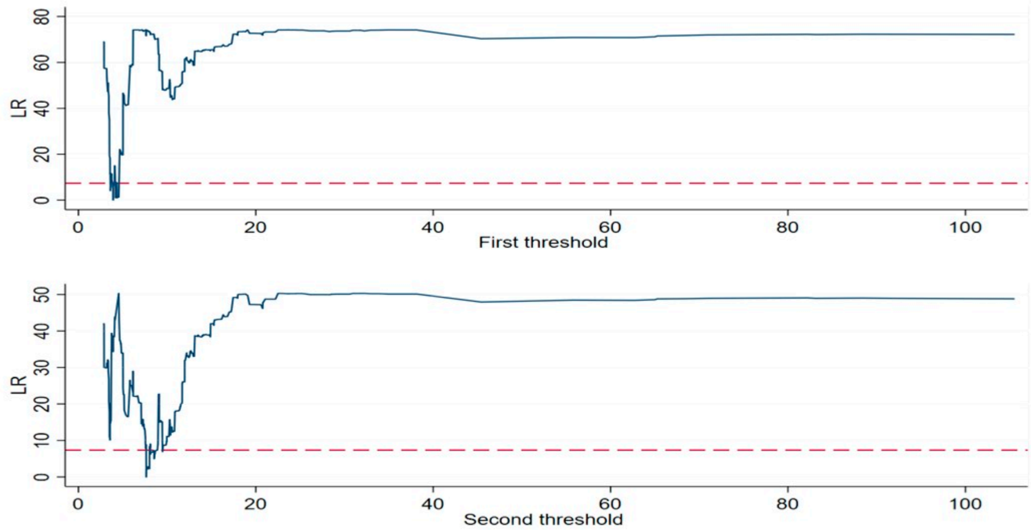

Figure 2. Threshold Likelihood Statistics of *L.Tech*.

Table 5. Results of the Panel Threshold Regression Analysis.

	Dependent Variable: CE	
	(1) Tech	**(2) L.Tech**
Tech (Envr $\leq$ threshold$_1$)	1.025 *** (0.099)	
Tech (threshold$_1$ < Envr $\leq$ threshold$_2$)	0.194 *** (0.056)	
Tech (Envr > threshold$_2$)	−0.152 *** (0.032)	
$(\text{Tech})_{-1}$ (Envr $\leq$ threshold$_1$)		1.225 *** (0.135)
$(\text{Tech})_{-1}$ (threshold$_1$ < Envr $\leq$ threshold$_2$)		0.195 *** (0.066)
$(\text{Tech})_{-1}$ (Envr > threshold$_2$)		−0.195 *** (0.039)
Constant	577 (1658)	1831 (1771)
Control variables	Yes	Yes
Year FE	Yes	Yes
Province FE	Yes	Yes
R^2	0.531	0.487
N	480	450

Notes: (1) Robust standard errors are in parentheses; (2) "***" denotes statistical significance at the 1% level; (3) the number of bootstrapping iterations for the likelihood ratio test was 300.

4.3. Endogenous Discussion

An inverse causal link between green innovation and construction-related carbon emissions may exist. In other words, higher construction carbon emissions may push the construction industry into green innovation, or there may be measurement errors or omitted variables. The existence of an endogenous problem means that the estimation results of model (4) are biased. As a result, we estimated our model (4) using the generalized two-step method-of-moments (GMM) estimator developed by Arellano and Bond (1991), which allowed us to correct endogeneity using instruments. This included constructing instrumental variables (IVs) using historical data on green innovation.

Green innovation's first-order and second-order lag terms were used as IVs in the two-step GMM regression. In Table 6, "first" and "second" indicate the results of the first- and second-stage regressions, respectively. As expected, each IV mentioned above had a substantial favorable impact on *Tech*. Furthermore, the IVs were plausible because the F-statistics in Table 6 exceed 10. This demonstrates that the IV selection is logical. The findings indicate that *Tech* considerably decreases *CE*, validating the dependability of the baseline estimate results. At the bottom of Table 6, you will see the validation test results for the IVs. The findings imply that concerns over inadequate variable identification and IVs can be ruled out. Therefore, the estimations for GMM2s are reliable.

Table 6. Instrumental-Variable Regression Results.

Dependent Variable:	**Tech**	**CE**	**Tech**	**CE**
Instrumental Variable:	**L.Tech**		**L2.Tech**	
	(1) **First**	**(2)** **Second**	**(1)** **First**	**(2)** **Second**
Tech		−0.187 *** (0.047)		−0.177 *** (0.050)
L.Tech	1.025 *** (0.080)			
L2.Tech			0.987 *** (0.115)	
F-test	164.760		74.000	
p-value	0.000		0.000	
Under-identification test				
Kleibergen–Paap rk LM-statistic		35.207 ***		36.411 ***
Weak instrumental variable test				
Cragg-Donald Wald F-statistic		1627.022		753.154
Stock–Yogo weak ID test critical values		16.380 (10%)		16.380 (10%)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
R^2		0.327		0.290
N	480	450	420	420

Notes: (1) Robust standard errors are in parentheses; (2) "***" denotes statistical significance at the 1% level; (3) the main function of the under-identification test is to check whether the instrumental variables are sufficiently valid to avoid unreliable estimation results due to inadequate instrumental variables. Under-identification of instrumental variables may result in imprecise, statistically insignificant, or biased estimates of regression coefficients; (4) the main function of the weak instrumental variable test is to test whether the instrumental variable is sufficiently strong to avoid unreliable estimation results due to the instrumental variable being underpowered. If the instrumental variable is strong, it may lead to accurate estimates of the regression coefficients, large standard errors, or biased estimation effects.

4.4. Robustness Check

We executed a set of robustness assessments to further validate our findings' dependability. Table 7 displays the results of the regression.

(1) The time window was extended. This paper extended the time examination window by treating the explained variable *CE* in a period ahead and two periods ahead. Table 7's columns (1) and (2) suggest that both estimated coefficients for *Tech* were notably negative. This suggests that the study findings remained unchanged after extending the time window.

(2) The control variables were indented. To exclude outliers in the control variables, all control variables were bilaterally shrunk by 1% at the top and bottom. In column (3) of Table 7 are shown the regression findings for the independent-variable tailoring, with a significantly negative regression coefficient for *Tech*.

(3) We evaluated the lagging terms of the *Tech* and the extreme values of the *CE*. Given the possible non-randomness, outliers, and time specificity of the study sample, all of which may impact the study results, the robustness of the study results was examined using two approaches, lagged terms and outliers, to further enhance the scientific validity of the analysis results. It may take years for green innovation to reach its full potential, so green innovation variables with a one-period lag were

selected to examine the possible time-lag effect. To explore possible variability in the CO_2 abatement process in the construction industry, the highest carbon emission value of 1% was eliminated. Table 7 contains the regression findings in columns (4) and (5). The *Tech* regression coefficient is significantly negative, and there is a temporal lag between *Tech* and the *CE* process in the building business. The *Tech* regression coefficient remains notably negative when eliminating extreme values.

(4) The impact of other environmental policies was considered. China implemented its first pilot policies for low-carbon provinces and cities in July 2010 and for carbon emissions trading in 2013 and a pilot policy for energy-use-rights trading in 2016. These measures have contributed to decreased energy use in the construction industry and increased green innovation. They may encourage communities to construct an industrial system with a smaller carbon footprint and to promote green and low-carbon lifestyles and consumption patterns. This may skew the appraisal of environmentally friendly innovations toward carbon reduction. To accurately identify the environmental effects of green innovation, interference from other similar policies must be excluded. This article includes interaction variables in the baseline regression for provinces participating in the pilot project between 2005 and 2020. Considering the first batch of low-carbon provincial and municipal pilot policies, carbon-emissions trading policies, and energy-use-rights trading pilot policies in turn, columns (6) to (8) of Table 7 reflect the impact of *Tech* on *CE*. The results show that the conclusions remain robust after excluding other policy disturbances.

(5) The impact of the COVID-19 pandemic was also considered. This paper excluded data for 2019 and 2020 from the COVID-19 period and generated dummy variables for 2019 and 2020 for separate two-way fixed-effects model regressions. Table A1 in Appendix A reports the results. The results were still significantly negative. This indicates that the results of this paper were not influenced by COVID-19.

Table 7. Robustness-Check Results.

	Dependent Variable:							
	F.CE	**F2.CE**	**CE**	**CE**	**CE**	**CE**	**CE**	**CE**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
L.Tech				−0.191 ** (0.078)				
Tech	−0.187 *** (0.067)	−0.171 *** (0.060)	−0.226 ** (0.082)		−0.182 ** (0.072)	−0.168 ** (0.073)	−0.185 ** (0.070)	−0.186 ** (0.072)
D_T_1						349.458 (222.789)		
D_T_2							152.979 (165.617)	
D_T_3								519.620 * (299.110)
Constant	−1252 (4644)	−2653 (4514)	68 (4948)	−87 (4935)	−295 (4851)	68.042 (4717.596)	40.484 (4853.225)	423.074 (4444.671)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.301	0.267	0.356	0.324	0.356	0.381	0.357	0.387
N	450	420	480	450	476	480	480	480

Notes: (1) Robust standard errors are in parentheses; (2) "***", "**", and "*" denote statistical significance at the 1%, 5%, and 10% levels, respectively. (3) "D_T_1", "D_T_2", and "D_T_3" denote the regression results of joining the first batch of low-carbon provincial and municipal pilot policies, carbon-emissions trading policies, and energy-use-rights trading pilot policies, respectively.

4.5. Intermediary Effect

The effect of *Tech* on the *CE* of the construction sector was examined. The bootstrap test and the recursive equation can be used to conduct tests for mediating effects. In pursuit of the robustness of results, using the bootstrap test and the recursive equation, the panel data were fitted to validate the mediating function of environmental regulation in its transmission process. The first three columns of Table 8 show the stepwise regression method's results. In contrast, the regression results of the Sobel and bootstrap method are displayed in column (4).

Table 8. Results of Mediation-Effect Analysis.

	Dependent Variable:			
	CE	**lnEnvr**	**CE**	**CE**
	(1)	**(2)**	**(3)**	**(4)**
Tech	−0.184 ** (0.073)	0.233 *** (0.048)	−0.026 (0.057)	−0.026 (0.031)
lnEnvr			−0.674 *** (0.242)	−0.674 *** (0.036)
ACME				−0.157 *** [−0.206, −0.108]
ADE				−0.026 [−0.078, 0.025]
TOTAL				−0.184 *** [−0.258, −0.109]
Percentage mediated (%)				85.669
Constant	−251 (4837)	−116 (4101)	−329 (2947)	193 (1698)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
R^2	0.354	0.474	0.648	0.895
N	480	480	480	480

Notes: (1) Robust standard errors are in parentheses; (2) "***" and "**" denote statistical significance at the 1% and 5% levels, respectively; (3) "ACME", "ADE", and "TOTAL" denote average causal mediation effect, average direct effect, and total effect, respectively. The estimation results (standard-deviation effects) and 95% confidence intervals (in square brackets) were obtained based on Imai et al. (2010) [68] and Tingley et al. (2015) [69]; the number of simulations was 1000.

Table 8 shows the test results of the mediating effect of environmental regulations. At the 5% significance level, the technology in column (1) was considered negative, showing that *Tech* has a major impact on *CE*. The *Tech* value in column (2) is very positive, indicating that green innovation is integrally tied to environmental legislation. Including environmental regulation in column (3) resulted in a coefficient of -0.026 for *Tech*. However, the data for *lnEnvr* passed the 1% significance test. This indicated that environmental regulation can reduce carbon emissions and act as a mediator in Tech and CE's influence mechanism. In column 4, the effect of *Tech* on *CE* is statistically distinguishable from zero. In addition, the ACME of environmental regulation decreases carbon emissions by 0.157 standard deviations, which is empirically significant (see confidence intervals for 95%) and represents 85.669% of the overall impact, making the overall effect greater than the ADE. Despite this, the direct effect of *Tech* on *CE* is statistically insignificant (see 95% confidence ranges). Consistent with earlier regression findings, *Tech* can only provide carbon reduction benefits via *lnEnvr*. This facilitates the enhancement of carbon abatement. According to Porter's premise, green innovation further reduces carbon emissions in the building sector through environmental legislation. The fully mediated role of *lnEnvr* suggests that the more stringent the environmental regulation intensity, the greater the carbon-reduction effect of green innovation.

4.6. Heterogeneity

4.6.1. Regional Heterogeneity

Depending on economic growth, population size, and other macroeconomic factors, the effect of *Tech* on *CE* in the building industry may also be varied. Therefore, it was also necessary to perform a heterogeneity analysis for these differences.

Referring to standard practices in the existing literature, we divided the study sample into three regions, East, Central, and West, denoted as region1, region2, and region3. Table 9 presents the results of the regression.

Table 9. Regional Heterogeneity Regression Results.

	Dependent Variable: CE		
	(1) Eastern	**(2) Central**	**(3) Western**
Tech	−0.121 ***	0.194 *	0.311
	(0.035)	(0.087)	(0.198)
Constant	−3380	−4097	13,175 ***
	(3829)	(4231)	(2124)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
R^2	0.400	0.878	0.876
N	192	144	144

Notes: (1) Robust standard errors are in parentheses; (2) "***" and "*" denote statistical significance at the 1% and 10% levels, respectively.

The regression findings of Table 9 suggested that *Tech* was substantially negative at the 1% level and highly positive at the 10% level in the Eastern and Central areas. In the Eastern area, carbon emissions fell by 12.1 units for every 1 unit rise in the *Tech* factor. Every 1-unit rise in the *Tech* factor in the Central region increased CO_2 emissions by 19.4 units. The Eastern region is more economically developed and has a better potential to absorb R&D funding than the Central and Western regions. It also has a huge influx of research expertise, making it easier for technical innovation to play a big role in carbon reduction in the building industry.

4.6.2. Heterogeneity of Innovation Factors

Financial input in science and technology (FIST) and human capital support green innovation and are important factors driving the industry to achieve carbon-emissions reduction. We investigated whether the CO_2 abatement effect of green innovation is characteristically varied between different levels of FIST and human capital. The number of survey and design institutions and personnel in the construction industry were used to represent human capital. The proportion of the public budget allocated to science and technology expenditures shows the financial investment in research and technology. Based on the medians, provinces were divided into high and low phases.

Table 10's columns (1) and (2) show the regression findings for financial input to research and technology. Table 10's columns (3), (4), (5), and (6) detail the human-capital regression findings. The findings indicate that an increase in *Tech* considerably decreases *CE* in provinces with high-tech financial inputs and human resources.

4.6.3. Heterogeneity of Development Types

The economic growth of resource-based provinces is primarily based on factor inputs, such as labor and mineral resources, and industries are mostly heavy-chemical industries. There are low levels of technological innovation in these provinces. Specifically, the growth of green innovation needs to be improved in resource-rich regions, which resources contribute to their high carbon emissions. So, then, have green solutions significantly decreased carbon emissions in the building sector in areas with abundant natural resources? The regression results for developmental-type heterogeneity are presented in the last two columns of Table 10. The estimated coefficients for *Tech* are significantly negative in columns (7) and (8). This means that the increase in eco-friendly technologies may significantly cut CO_2 emissions from the construction industry in resource-poor areas. Still, the impact will be greater in natural-resource-rich provinces.

Table 10. Heterogeneity of Innovation Factors and Heterogeneity of Development-Type Regression Results.

	Dependent Variable: CE							
	(1) Type1	**(2) Type2**	**(3) Type3**	**(4) Type4**	**(5) Type5**	**(6) Type6**	**(7) Prov1**	**(8) Prov2**
Tech	−0.139 **	0.584 **	−0.217 *	−0.000	−0.184 *	−0.438	−0.108 **	−0.781 *
	(0.060)	(0.273)	(0.125)	(0.299)	(0.094)	(0.348)	(0.048)	(0.353)
Constant	−7825	2688	−7230	7288	−14,212 *	5213	−363	2718
	(9873)	(5589)	(5633)	(5012)	(7797)	(3391)	(5933)	(6203)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.364	0.510	0.411	0.436	0.446	0.507	0.511	0.563
N	240	240	240	240	240	240	320	160

Notes: (1) Robust standard errors in parentheses; (2) "**" and "*" denote statistical significance at the 5% and 10% levels, respectively; (3) "Type1" denotes high-tech financial inputs, "Type2" denotes low-tech financial inputs, "Type3" denotes high human capital-I, "Type4" denotes low human capital-I, "Type5" denotes high human capital-II, "Type6" denotes low human capital-II, "Prov1" denotes non-resource-based, and "Prov2" denotes resource-based, respectively; (4) "I" and "II" denote the number of survey and design institutions and personnel in the construction industry in human capital, respectively.

5. Discussion

Based on this study, we have made some new findings.

(1) The growth in green innovation has successfully decreased CO_2 emissions in the inter-provincial building sector. CO_2 emissions come largely from fossil-fuel combustion in industries with high carbon emissions. The production benefits of higher levels of technological innovation may compensate for the investment costs of combating emissions [70]. Aware of the global warming challenge caused by "fast growth, high energy usage, and high carbon dioxide emissions", the Chinese government has rapidly applied technological advances to improve industrial efficiency and curb CO_2 emissions. Through technology development, the application of low-carbon products, expanded green productive capacity, multiple different spillover effects, cost reductions, and specialized labor division, green innovation can reduce the amount of energy consumed in the construction sector and the CO_2 emissions caused by low productivity, high energy consumption, and high input. Therefore, green technical innovation can optimize the industrial structure, eliminate polluting industries, improve energy-consumption efficiency, and meet the objective of attaining energy conservation, which will influence the industry's carbon emissions ineluctably. In short, the carbon emissions of the building industry can be drastically reduced by increasing the degree of green innovation.

(2) A certain amount of environmental control facilitates enhancing the potential of green technologies to reduce dioxide emissions. This may have varying effects depending on the extent of environmental control. (1) As the amount of environmental regulation increases, so does the demand for punitive measures, the attractiveness of the incentives, and the motivation to cut carbon emissions. Therefore, more construction firms will reduce some of their production-expansion funds for research and development, while also tending to use new technologies to improve the cleanliness of construction production, thereby achieving CO_2 emissions reduction and meeting governmental environmental regulatory requirements. (2) In places where environmental

regulations are lax, construction companies are more willing to invest in expanding production. Since the earnings from such growth may more than balance the costs of environmental regulation, construction companies are less likely to research and implement technical solutions to minimize carbon emissions in the building sector. China's strong environmental policies have helped to reduce carbon emissions globally. However, environmental management is a long process that should not be achieved by regulatory policies alone, and the link between technological innovation and environmental regulations should be emphasized [71].

(3) Green innovation exploits environmental regulations to provide additional incentives for carbon emissions in the building sector. With a high degree of environmental regulation, construction businesses think that the penalties for polluting emissions are too severe, causing the costs of emissions to far outweigh the costs of lowering emissions. Consequently, businesses are more ready to invest in research and development or adopt new eco-friendly technologies to increase the cleanliness of building production, thus lowering CO_2 emissions and internalizing external expenses.

(4) Research reveals that (1) green innovation substantially influences dioxide reduction in the eastern building sector. In Eastern China, the economy is more developed, the awareness of the environment is greater, technology is more sophisticated, and technical research and development facilities are well-established. Establishing stringent environmental legislation and green innovation might amplify the impact of CO_2 reduction in the building sector. For the Central and Western regions, which are primarily focused on the development of heavy industries and have long relied on a high-energy-consumption economic growth model, the effect of technological innovation guidance needs to be strong. (2) Increased levels of green innovation significantly reduce carbon emissions in high-tech financial investment and high-human-capital provinces. Following China's regulations regarding subsidies for energy conservation and dioxide-abatement projects, the fourteenth 5-year plan has continued to increase expenditures in research, technology, and human capital. Through autonomous research and development of cleaner production technologies and the absorption of energy-saving technologies, the "double-high" companies will create suitable energy-saving technologies and cleaner production models. (3) Resource-based provinces have greater potential to reduce emissions than non-resource-based provinces. In other words, both forms of carbon emissions have been reduced, but the decline in the former is much more pronounced. With economic growth and regional mobility, the degree of eco-friendly technologies in the construction sector in resource-based provinces has progressively grown, as has the expansion of technological applications. Regarding national policy and transitional development, their industries are progressively moving from a resource-intensive, highly polluting, and energy-intensive kind to a technology-intensive one. They are continually overcoming the "resource curse" challenge, and the degree to which eco-friendly technologies are integrated into the growth of these firms is increasing. However, the increasing investment in scientific and technical expertise and funding for R&D in the building industry of these provinces has increased their growth in terms of green innovation. The energy-consumption structure has moved from using fossil fuels to using clean and renewable energy. Due to these characteristics, green innovation may majorly impact carbon reduction.

This article comprehensively reviews the Chinese provincial building industry's efforts to reduce dioxide emissions. It helps important ministries, governments, and enterprises comprehend technological techniques for lowering dioxide emissions. Based on the viewpoint of emissions-reduction pathways, the findings may serve as a policy reference for the future direction of CO_2 emissions abatement in China's building sector. This paper's study framework and technique apply to examination of the construction industry in China and other sectors and nations.

6. Conclusions and Implications

6.1. Conclusions

In the context of carbon peaking and neutrality, green innovation is essential for lowering carbon emissions in the context of carbon peaking and neutrality. This study investigated the linear and non-linear relationships between green innovation and CO_2 emissions in the construction sector using panel data from 2005 to 2020 for 30 Chinese regions. Meanwhile, we investigated the moderating influence that environmental regulation has on green innovation. In addition, we empirically examined the potential heterogeneity of green innovation in terms of CO_2 emissions by reference to geography, innovation factors, and types of development. The following are the primary findings and policy suggestions.

We obtained four results:

(1) There is a negative association between green innovation and dioxide emissions in China's construction business. This study found a significant impact on the total amount but did not find a significant impact on the proportion of emissions reduction. Further research is needed.
(2) The greater the severity of environmental regulation above the second barrier, the greater the abatement effect of green innovation.
(3) Environmental regulation substantially and beneficially moderates the influence of green innovation on CO_2 emissions.
(4) Only in the East can technology substantially negatively affect regional-construction-related dioxide emissions. In contrast, the degree of green innovation in high-tech financial investment and high-human-capital regions can cut carbon emissions by a substantial amount. Increased green innovation can significantly cut carbon emissions in resource-poor provinces but has a greater abatement impact in resource-rich provinces.

6.2. Implications

The above conclusions have some policy implications:

(1) Policy guidance should be considered to strongly support the introduction, research, and development of green technologies.
(2) We should rationalize environmental regulation policies and improve environmental regulations. Accelerating the implementation of environmental tax policies and establishing a strict technology and industry access mechanism is important.
(3) We should enhance the technical content of emissions abatement and produce a "win-win" scenario for regional growth and technological advancement in CO_2 emissions abatement in the construction industry.

The limitations of this article may indicate future research topics. First, this study only covered provincial research scales. Selecting smaller scales, such as the city, would have made the results more comprehensive. Carbon emissions at the microscopic level might be a topic of future study. Second, all the energy each province's building sector utilized was taken for the computation of direct carbon emissions. However, secondary energy carbon emissions, such as electricity consumption and thermal energy, were not considered. Specific indirect consumption and emissions were also excluded. This research only proves that total growth in green innovation can bring about carbon-reduction effects and does not show the impact of proportional changes in green innovation. One possible reason is that the patterns discovered in this article are typical non-linear relationships. Considering regional differences, the impact of a 1% increase in green patent levels may exhibit significant differences. It is necessary to investigate further why this pattern only appears at the total level of green patent data and not proportionally. Future research should expand the scope of carbon-emissions measurement and consider indirect energy-consumption and emissions data.

Author Contributions: Conceptualization, Y.Y.; methodology, X.L.; software, X.L.; validation, Q.Q.; formal analysis, Y.Y.; investigation, X.L.; resources, Y.Y.; data curation, X.L.; writing—original draft preparation, X.L.; writing—review and editing, Y.Y.; visualization, Y.Y.; supervision, Q.Q. and Y.Y.; project administration, Y.Y.; funding acquisition, Y.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Zhejiang Provincial Natural Science Foundation of China (LQ22G030014 and LY20G010010); the Ministry of Education of Humanities and Social Science project (20JHQ060); the Soft Science Research Project of Zhejiang Province (2022C25030); the Science and Technology Innovation Activity Plan of college students in Zhejiang Province (2022R406A039); the National College Students' Innovative Entrepreneurial Training Program of China (202210338026); and the Audit research project of the Zhejiang Province Audit Department (202202003).

Data Availability Statement: Not applicable.

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

Appendix A

Table A1 indicates the results of other robustness tests, i.e., considering the impact during the COVID-19 pandemic.

Table A1. Regression Results after Excluding Time and Adding Dummy Variables.

	Dependent Variable: CE	
	(1) **FE1**	**(2)** **FE2**
Tech	−0.244 ***	−0.184 **
	(0.076)	(0.073)
D_T		−742.877
		(623.941)
Constant	2844.587	−251.175
	(4243.115)	(4837.315)
Control variables	Yes	Yes
Year FE	Yes	Yes
Province FE	Yes	Yes
R^2	0.384	0.354
N	420	480

Notes: (1) Robust standard errors in parentheses; (2) "***" and "**" denote statistical significance at the 1% and 5% levels, respectively; (3) column (1) indicates the exclusion of 2019 and 2020, and column (2) indicates the inclusion of year dummy variables in the two-way fixed-effects model.

Appendix B

Table A2. Results obtained when CE is taken logarithmically.

	Dependent Variable: lnCE			
	(1) **FE**	**(2)** **FE_r**	**(3)** **FE_bootstrap**	**(4)** **FE_dt**
Tech	−0.085	−0.230 ***	−0.230 ***	−0.151 ***
	(0.065)	(0.047)	(0.039)	(0.037)
lnCongdp		305.583	305.583	398.635
		(426.283)	(308.064)	(345.537)
lnConjo		−26.506	−26.506	78.488
		(141.476)	(106.645)	(96.908)
Town		1821.976	1821.976	2353.374 **
		(2265.191)	(1292.519)	(1194.637)
Open		−5635.558 *	−5635.558 ***	−3399.564 **
		(3097.572)	(1707.662)	(1534.225)

Table A2. *Cont.*

	Dependent Variable: lnCE			
	(1) **FE**	**(2)** **FE_r**	**(3)** **FE_bootstrap**	**(4)** **FE_dt**
Rede		−3.094	−3.094 **	−3.778 **
		(2.901)	(1.514)	(1.542)
Indus		−4404.762	−4404.762	−2381.910
		(4607.237)	(3862.105)	(4069.888)
Pgdp		201.442	201.442	−29.259
		(550.116)	(334.086)	(340.673)
Pate		0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)
Scit		1.218	1.218 *	0.501
		(0.973)	(0.632)	(0.574)
Expe		−0.000	−0.000	0.001
		(0.001)	(0.001)	(0.001)
Budge		0.041	0.041	−0.005
		(0.085)	(0.038)	(0.043)
Constant	5629.692 ***	2122.339	2122.339	2100.004
	(92.867)	(4272.404)	(2085.192)	(2520.357)
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
R^2	0.434	0.503	0.503	
N	480	480	480	480

Notes: (1) Robust standard errors are in parentheses; (2) "***", "**", and "*" denote statistical significance at the 1%, 5%, and 10% levels, respectively.

References

1. Zhang, H.; Li, S. Carbon Emissions' Spatial-Temporal Heterogeneity and Identification from Rural Energy Consumption in China. *J. Environ. Manage.* **2022**, *304*, 114286. [CrossRef] [PubMed]
2. Bai, Y.; Deng, X.; Gibson, J.; Zhao, Z.; Xu, H. How Does Urbanization Affect Residential CO_2 Emissions? An Analysis on Urban Agglomerations of China. *J. Clean. Prod.* **2019**, *209*, 876–885. [CrossRef]
3. Dong, Z.; Xia, C.; Fang, K.; Zhang, W. Effect of the Carbon Emissions Trading Policy on the Co-Benefits of Carbon Emissions Reduction and Air Pollution Control. *Energy Policy* **2022**, *165*, 112998. [CrossRef]
4. Kim, S.E.; Xie, Y.; Dai, H.; Fujimori, S.; Hijioka, Y.; Honda, Y.; Hashizume, M.; Masui, T.; Hasegawa, T.; Xu, X.; et al. Air Quality Co-Benefits from Climate Mitigation for Human Health in South Korea. *Environ. Int.* **2020**, *136*, 105507. [CrossRef] [PubMed]
5. Demircan Çakar, N.; Gedikli, A.; Erdoğan, S.; Yıldırım, D.Ç. A Comparative Analysis of the Relationship between Innovation and Transport Sector Carbon Emissions in Developed and Developing Mediterranean Countries. *Environ. Sci. Pollut. Res.* **2021**, *28*, 45693–45713. [CrossRef]
6. Du, Q.; Deng, Y.; Zhou, J.; Wu, J.; Pang, Q. Spatial Spillover Effect of Carbon Emission Efficiency in the Construction Industry of China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 2466–2479. [CrossRef]
7. Erdogan, S. Dynamic Nexus between Technological Innovation and Building Sector Carbon Emissions in the BRICS Countries. *J. Environ. Manag.* **2021**, *293*, 112780. [CrossRef]
8. Çakar, N.D.; Gedikli, A.; Erdoğan, S.; Yıldırım, D.Ç. Exploring the Nexus between Human Capital and Environmental Degradation: The Case of EU Countries. *J. Environ. Manag.* **2021**, *295*, 113057. [CrossRef]
9. Solarin, S.A.; Bello, M.O.; Tiwari, A.K. The Impact of Technological Innovation on Renewable Energy Production: Accounting for the Roles of Economic and Environmental Factors Using a Method of Moments Quantile Regression. *Heliyon* **2022**, *8*, e09913. [CrossRef]
10. Erdoğan, S.; Yıldırım, S.; Yıldırım, D.Ç.; Gedikli, A. The Effects of Innovation on Sectoral Carbon Emissions: Evidence from G20 Countries. *J. Environ. Manag.* **2020**, *267*, 110637. [CrossRef]
11. Gao, P.; Yue, S.; Chen, H. Carbon Emission Efficiency of China's Industry Sectors: From the Perspective of Embodied Carbon Emissions. *J. Clean. Prod.* **2021**, *283*, 124655. [CrossRef]
12. Cheng, C.; Ren, X.; Dong, K.; Dong, X.; Wang, Z. How Does Technological Innovation Mitigate CO_2 Emissions in OECD Countries? Heterogeneous Analysis Using Panel Quantile Regression. *J. Environ. Manag.* **2021**, *280*, 111818. [CrossRef] [PubMed]
13. Yu, C.-H.; Wu, X.; Zhang, D.; Chen, S.; Zhao, J. Demand for Green Finance: Resolving Financing Constraints on Green Innovation in China. *Energy Policy* **2021**, *153*, 112255. [CrossRef]
14. Sun, L.; Miao, C.; Yang, L. Ecological-Economic Efficiency Evaluation of Green Technology Innovation in Strategic Emerging Industries Based on Entropy Weighted TOPSIS Method. *Ecol. Indic.* **2017**, *73*, 554–558. [CrossRef]

15. Ooba, M.; Hayashi, K.; Fujii, M.; Fujita, T.; Machimura, T.; Matsui, T. A Long-Term Assessment of Ecological-Economic Sustainability of Woody Biomass Production in Japan. *J. Clean. Prod.* **2015**, *88*, 318–325. [CrossRef]
16. Kunapatarawong, R.; Martinez-Ros, E. Towards Green Growth: How Does Green Innovation Affect Employment? *Res. Policy* **2016**, *45*, 1218–1232. [CrossRef]
17. Chen, Z.; Zhang, X.; Chen, F. Do Carbon Emission Trading Schemes Stimulate Green Innovation in Enterprises? Evidence from China. *Technol. Forecast. Soc. Chang.* **2021**, *168*, 120744. [CrossRef]
18. Xu, L.; Fan, M.; Yang, L.; Shao, S. Heterogeneous Green Innovations and Carbon Emission Performance: Evidence at China's City Level. *Energy Econ.* **2021**, *99*, 105269. [CrossRef]
19. Du, K.; Li, P.; Yan, Z. Do Green Technology Innovations Contribute to Carbon Dioxide Emission Reduction? Empirical Evidence from Patent Data. *Technol. Forecast. Soc. Chang.* **2019**, *146*, 297–303. [CrossRef]
20. Guo, Y.; Xia, X.; Zhang, S.; Zhang, D. Environmental Regulation, Government R&D Funding and Green Technology Innovation: Evidence from China Provincial Data. *Sustainability* **2018**, *10*, 940. [CrossRef]
21. Ganda, F. The Impact of Innovation and Technology Investments on Carbon Emissions in Selected Organisation for Economic Co-Operation and Development Countries. *J. Clean. Prod.* **2019**, *217*, 469–483. [CrossRef]
22. Bai, C.; Feng, C.; Yan, H.; Yi, X.; Chen, Z.; Wei, W. Will Income Inequality Influence the Abatement Effect of Renewable Energy Technological Innovation on Carbon Dioxide Emissions? *J. Environ. Manag.* **2020**, *264*, 110482. [CrossRef] [PubMed]
23. Weina, D.; Gilli, M.; Mazzanti, M.; Nicolli, F. Green Inventions and Greenhouse Gas Emission Dynamics: A Close Examination of Provincial Italian Data. *Environ. Econ. Policy Stud.* **2016**, *18*, 247–263. [CrossRef]
24. Yu, Y.; Radulescu, M.; Ifelunini, A.I.; Ogwu, S.O.; Onwe, J.C.; Jahanger, A. Achieving Carbon Neutrality Pledge through Clean Energy Transition: Linking the Role of Green Innovation and Environmental Policy in E7 Countries. *Energies* **2022**, *15*, 6456. [CrossRef]
25. Jia, L.; Hu, X.; Zhao, Z.; He, B.; Liu, W. How Environmental Regulation, Digital Development and Technological Innovation Affect China's Green Economy Performance: Evidence from Dynamic Thresholds and System GMM Panel Data Approaches. *Energies* **2022**, *15*, 884. [CrossRef]
26. Fong, W.; Sun, Y.; Chen, Y. Examining the Relationship between Energy Consumption and Unfavorable CO_2 Emissions on Sustainable Development by Going through Various Violated Factors and Stochastic Disturbance-Based on a Three-Stage SBM-DEA Model. *Energies* **2022**, *15*, 569. [CrossRef]
27. Mohsin, M.; Kamran, H.W.; Nawaz, M.A.; Hussain, M.S.; Dahri, A.S. Assessing the Impact of Transition from Nonrenewable to Renewable Energy Consumption on Economic Growth-Environmental Nexus from Developing Asian Economies. *J. Environ. Manage.* **2021**, *284*, 111999. [CrossRef]
28. Lin, B.; Ma, R. Green Technology Technology Innovations, Urban Innovation Environment and CO_2 Emission Reduction in China: Fresh Evidence from a Partially Linear Functional-Coefficient Panel Model. *Technol. Forecast. Soc. Chang.* **2022**, *176*, 121434. [CrossRef]
29. Dauda, L.; Long, X.; Mensah, C.N.; Salman, M. The Effects of Economic Growth and Innovation on CO_2 Emissions in Different Regions. *Environ. Sci. Pollut. Res.* **2019**, *26*, 15028–15038. [CrossRef]
30. Chen, Y.; Lee, C.-C. Does Technological Innovation Reduce CO_2 Emissions?Cross-Country Evidence. *J. Clean. Prod.* **2020**, *263*, 121550. [CrossRef]
31. Zimon, G.; Zimon, D. The Impact of Purchasing Group on the Profitability of Companies Operating in the Renewable Energy Sector-The Case of Poland. *Energies* **2020**, *13*, 6588. [CrossRef]
32. Jiang, T.; Li, S.; Yu, Y.; Peng, Y. Energy-Related Carbon Emissions and Structural Emissions Reduction of China's Construction Industry: The Perspective of Input–Output Analysis. *Environ. Sci. Pollut. Res.* **2022**, *29*, 39515–39527. [CrossRef] [PubMed]
33. Zhang, S.; Li, Z.; Ning, X.; Li, L. Gauging the Impacts of Urbanization on CO_2 Emissions from the Construction Industry: Evidence from China. *J. Environ. Manag.* **2021**, *288*, 112440. [CrossRef] [PubMed]
34. Lai, X.; Lu, C.; Liu, J. A Synthesized Factor Analysis on Energy Consumption, Economy Growth, and Carbon Emission of Construction Industry in China. *Environ. Sci. Pollut. Res.* **2019**, *26*, 13896–13905. [CrossRef] [PubMed]
35. Dechezleprêtre, A.; Glachant, M. Does Foreign Environmental Policy Influence Domestic Innovation? Evidence from the Wind Industry. *Environ. Resour. Econ.* **2014**, *58*, 391–413. [CrossRef]
36. Porter, M.E.; van der Linde, C. Toward a New Conception of the Environment-Competitiveness Relationship. *J. Econ. Perspect.* **1995**, *9*, 97–118. [CrossRef]
37. Guo, Q.; Su, Z.; Chiao, C. Carbon Emissions Trading Policy, Carbon Finance, and Carbon Emissions Reduction: Evidence from a Quasi-Natural Experiment in China. *Econ. Chang. Restruct.* **2022**, *55*, 1445–1480. [CrossRef]
38. Lin, S.; Sun, J.; Marinova, D.; Zhao, D. Evaluation of the Green Technology Innovation Efficiency of China's Manufacturing Industries: DEA Window Analysis with Ideal Window Width. *Technol. Anal. Strateg. Manag.* **2018**, *30*, 1166–1181. [CrossRef]
39. Luo, Q.; Miao, C.; Sun, L.; Meng, X.; Duan, M. Efficiency Evaluation of Green Technology Innovation of China's Strategic Emerging Industries: An Empirical Analysis Based on Malmquist-Data Envelopment Analysis Index. *J. Clean. Prod.* **2019**, *238*, 117782. [CrossRef]
40. Wu, H.; Li, Y.; Hao, Y.; Ren, S.; Zhang, P. Environmental Decentralization, Local Government Competition, and Regional Green Development: Evidence from China. *Sci. Total Environ.* **2020**, *708*, 135085. [CrossRef]

41. Wu, Y.; Sun, C. A Research on the Green Technology Innovation of the Cemetery Industry. In *Proceedings of the Isbim: 2008 International Seminar on Business and Information Management*; Luo, Q., Ed.; IEEE Computer Society: Los Alamitos, CA, USA, 2009; Volume 1, pp. 147–150.
42. Demir, C.; Cergibozan, R.; Ari, A. Environmental Dimension of Innovation: Time Series Evidence from Turkey. *Environ. Dev. Sustain.* **2020**, *22*, 2497–2516. [CrossRef]
43. Dinda, S. Environmental Kuznets Curve Hypothesis: A Survey. *Ecol. Econ.* **2004**, *49*, 431–455. [CrossRef]
44. Chang, K.; Liu, L.; Luo, D.; Xing, K. The Impact of Green Technology Innovation on Carbon Dioxide Emissions: The Role of Local Environmental Regulations. *J. Environ. Manag.* **2023**, *340*, 117990. [CrossRef] [PubMed]
45. Porter, M.E. The Role of Location in Competition. *Int. J. Econ. Bus.* **1994**, *1*, 35–40. [CrossRef]
46. Xu, Y.; Dong, Z.; Wu, Y. The Spatiotemporal Effects of Environmental Regulation on Green Innovation: Evidence from Chinese Cities. *Sci. Total Environ.* **2023**, *876*, 162790. [CrossRef] [PubMed]
47. Lee, S.; Chong, W.O. Causal Relationships of Energy Consumption, Price, and CO_2 Emissions in the U.S. Building Sector. *Resour. Conserv. Recycl.* **2016**, *107*, 220–226. [CrossRef]
48. Su, Y.; Zou, Z.; Ma, X.; Ji, J. Understanding the Relationships between the Development of the Construction Sector, Carbon Emissions, and Economic Growth in China: Supply-Chain Level Analysis Based on the Structural Production Layer Difference Approach. *Sustain. Prod. Consum.* **2022**, *29*, 730–743. [CrossRef]
49. Huang, L.; Krigsvoll, G.; Johansen, F.; Liu, Y.; Zhang, X. Carbon Emission of Global Construction Sector. *Renew. Sustain. Energy Rev.* **2018**, *81*, 1906–1916. [CrossRef]
50. Li, X.-J.; Lai, J.; Ma, C.; Wang, C. Using BIM to Research Carbon Footprint during the Materialization Phase of Prefabricated Concrete Buildings: A China Study. *J. Clean. Prod.* **2021**, *279*, 123454. [CrossRef]
51. Chastas, P.; Theodosiou, T.; Bikas, D. Embodied Energy in Residential Buildings-towards the Nearly Zero Energy Building: A Literature Review. *Build. Environ.* **2016**, *105*, 267–282. [CrossRef]
52. Shan, Y.; Liu, J.; Liu, Z.; Xu, X.; Shao, S.; Wang, P.; Guan, D. New Provincial CO_2 Emission Inventories in China Based on Apparent Energy Consumption Data and Updated Emission Factors. *Appl. Energy* **2016**, *184*, 742–750. [CrossRef]
53. Ehrlich, P.R.; Holdren, J.P. Impact of Population Growth. *Science* **1971**, *171*, 1212–1217. [CrossRef] [PubMed]
54. Dietz, T.; Rosa, E. Rethinking the Environmental Impacts of Population, Affluence and Technology. *Hum. Ecol. Rev.* **1994**, *1*, 277–300.
55. Zhu, C.; Chang, Y.; Li, X.; Shan, M. Factors Influencing Embodied Carbon Emissions of China's Building Sector: An Analysis Based on Extended STIRPAT Modeling. *Energy Build.* **2022**, *255*, 111607. [CrossRef]
56. York, R.; Rosa, E.A.; Dietz, T. STIRPAT, IPAT and ImPACT: Analytic Tools for Unpacking the Driving Forces of Environmental Impacts. *Ecol. Econ.* **2003**, *46*, 351–365. [CrossRef]
57. Ma, M.; Yan, R.; Cai, W. An Extended STIRPAT Model-Based Methodology for Evaluating the Driving Forces Affecting Carbon Emissions in Existing Public Building Sector: Evidence from China in 2000–2015. *Nat. Hazards* **2017**, *89*, 741–756. [CrossRef]
58. Rubashkina, Y.; Galeotti, M.; Verdolini, E. Environmental Regulation and Competitiveness: Empirical Evidence on the Porter Hypothesis from European Manufacturing Sectors. *Energy Policy* **2015**, *83*, 288–300. [CrossRef]
59. Hansen, B.E. Sample Splitting and Threshold Estimation. *Econometrica* **2000**, *68*, 575–603. [CrossRef]
60. Berrone, P.; Fosfuri, A.; Gelabert, L.; Gomez-Mejia, L.R. Necessity as the Mother of 'green' Inventions: Institutional Pressures and Environmental Innovations. *Strateg. Manag. J.* **2013**, *34*, 891–909. [CrossRef]
61. Fu, L.; Yi, Y.; Wu, T.; Cheng, R.; Zhang, Z. Do Carbon Emission Trading Scheme Policies Induce Green Technology Innovation? New Evidence from Provincial Green Patents in China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 13342–13358. [CrossRef]
62. Zugravu, N.; Kheder, S.B. The Pollution Haven Hypothesis: A Geographic Economy Model in a Comparative Study. *Soc. Sci. Electron. Publ.* **2008**. [CrossRef]
63. Fan, J.; Zhou, L.; Zhang, Y.; Shao, S.; Ma, M. How Does Population Aging Affect Household Carbon Emissions? Evidence from Chinese Urban and Rural Areas. *Energy Econ.* **2021**, *100*, 105356. [CrossRef]
64. Qiu, S.; Wang, Z.; Liu, S. The Policy Outcomes of Low-Carbon City Construction on Urban Green Development: Evidence from a Quasi-Natural Experiment Conducted in China. *Sustain. Cities Soc.* **2021**, *66*, 102699. [CrossRef]
65. Li, W.; Ullah, S. Research and Development Intensity and Its Influence on Renewable Energy Consumption: Evidence from Selected Asian Economies. *Environ. Sci. Pollut. Res.* **2022**, *29*, 54448–54455. [CrossRef]
66. Wu, L.; Sun, L.; Qi, P.; Ren, X.; Sun, X. Energy Endowment, Industrial Structure Upgrading, and CO_2 Emissions in China: Revisiting Resource Curse in the Context of Carbon Emissions. *Resour. Policy* **2021**, *74*, 102329. [CrossRef]
67. Guo, X.; Deng, C.; Wang, D.; Du, X.; Li, J.; Wan, B. International Comparison of the Efficiency of Agricultural Science, Technology, and Innovation: A Case Study of G20 Countries. *Sustainability* **2021**, *13*, 2769. [CrossRef]
68. Imai, K.; Keele, L.; Yamamoto, T. Identification, Inference and Sensitivity Analysis for Causal Mediation Effects. *Stat. Sci.* **2010**, *25*, 51–71. [CrossRef]
69. Tingley, D.; Yamamoto, T.; Hirose, K.; Keele, L.; Imai, K. Mediation: R Package for Causal Mediation Analysis. *J. Stat. Softw.* **2014**, *59*, 1–38. [CrossRef]

70. Jiang, Z.; Wang, Z.; Zeng, Y. Can Voluntary Environmental Regulation Promote Corporate Technological Innovation? *Bus. Strategy Environ.* **2020**, *29*, 390–406. [CrossRef]
71. Ma, R.; Li, F.; Du, M. How Does Environmental Regulation and Digital Finance Affect Green Technological Innovation: Evidence From China. *Front. Environ. Sci.* **2022**, *10*, 928320. [CrossRef]