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Does green investment reduce carbon emissions? New evidence from partially linear functional-coefficient models

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ABSTRACT

Green investment (GI) has great potential to reach China's 'double carbon' target. However, it is still unknown what factors will govern the impact of GI on carbon emissions. This research relaxes the homogeneity and linearity assumed in traditional empirical models and adopts a newly developed partially linear functional-coefficient model to estimate the specific response function of GI on carbon emissions under regional heterogeneity. The results indicate that the role of GI plays a relatively greater role in the western and central regions than in the eastern regions. This highlights the latecomer advantage of the central and western regions under the 'double carbon' target. The beneficial effect of GI on carbon emission intensity is only apparent once the province's economic development level exceeds a certain threshold. For provinces with low GDP per capita, it is recommended to prioritize economic development. When the logarithm of the province's GDP per capita is higher than 9.70, we encourage strong GI. As the industrial structure continues to upgrade, the marginal effect of GI on carbon emissions will continue to increase after a key inflection point.

1. Introduction

Since the industrial revolution, human emissions of greenhouse gases into the atmosphere have been increasing year by year, which has led to a range of hazards such as rising sea levels, increasing frequency of extremely severe natural weather conditions, droughts, and agricultural destruction that are increasingly threatening human survival and causing widespread concern around the world [1,2]. The largest greenhouse gas in the atmosphere with the highest concentration is Carbon Dioxide (CO2), which has the strongest impact on global warming [3]. As a result, countries around the world have made reducing carbon emissions a top priority. China relies heavily on coal to meet its local energy demand [4], and its fast-growing economy has resulted in significant carbon emissions [5]. Against this background, China proclaimed its "double carbon" target in 2020, announcing its plan to limit CO2 emissions and work towards carbon neutrality or zero emissions targets for the year 2030 (the amount of CO2 emitted and the amount of CO2 naturally absorbed should be the same) by 2060 [6]. However, the task of simultaneously controlling emissions and addressing the associated harmful effects of carbon emissions is extremely challenging, and there is an urgent need to identify the key contributors to CO2 emissions [7].

Green investment (GI) is an investment model that incorporates environmental concerns into investment considerations in an effort to eliminate environmental problems associated with human activity [8]. Amid the growing problem of environmental degradation, GI plays an increasingly prominent place in the development of the global economy [9]. The European Union (EU) has made the "green

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transition" a key direction for development in its €750 billion economic recovery plan. The President of the United States has also announced a development plan to invest more than $2 trillion in key areas such as clean energy and green buildings [10]. GI is not only of great interest in developed countries but is also considered the best way to combat environmental pollution and degradation in developing countries [11]. China's serious environmental problems may hinder its future development [12]. The Chinese White Paper on Green Development in a New Era, published in 2023, mentions the need to encourage environmental restructuring of the modernization process and establish a green spatial pattern. In order to increase the level of sustainable development investment in China, it is imperative to analyze the role and influence of GI in the Chinese context [13] and verify whether GI can bring new momentum and opportunities for economic development in China.

China needs to achieve both energy efficiency and emission reductions while reducing the potential negative impacts of carbon emissions to meet its Paris Agreement commitment of reducing CO2 emissions by 60–65% in 2030 [7]. The concept of GI and its importance for environmental governance has received much attention in recent years [14]. The positive effects of GI have been the focus of previous research in terms of economic growth [8,15], firm performance [16,17], and sustainable development [13,18]. The potential impact of GI on climate change has been investigated in other papers [11,19] or the overall macro environment [20] from an ecological perspective. On the other hand, the factors influencing carbon emissions have also been widely studied. For example, Derindag et al. [21] focused on the impact of trade openness and foreign direct investment on carbon emissions. Wei et al. [22] found that there is a relationship between livestock economic development and carbon emissions. The study of Pu and Fei [23] showed that the digital economy increased residential carbon emissions. All the above studies provide inspiration for our research.

Although the ecological impact of GI is receiving increasing academic attention, the factors that govern the impact of GI on carbon emissions are still unknown. It has also been suggested that GI may have heterogeneous effects on the scale and magnitude of CO2 emissions in different regions of China [24,25]. As a result, in accordance with the regional context in China, it is essential to evaluate the effect of GI on CO2 emissions and to propose emission reduction solutions that have the characteristics of environmentally friendly economic development.

The present study is innovative and makes a contribution to the available research in terms of the below-mentioned points. First, the current research investigates the diverse effects of GI on CO2 emission intensity under various regional conditions in China, providing effective suggestions for the government and other actors to implement emission reduction measures. Second, this paper uses the partially linear functional-coefficient (PLFC) method. This is a new semiparametric model that relaxes previous linear assumptions about the functional form, thus reducing the risk of model misspecification and estimation bias. The study of this model provides new empirical evidence for the nonlinear effect between GI and carbon emissions and its mechanism and provides insights into the heterogeneity effect of economic development and industrial structure.

This article is structured as follows: Section 2 presents an overview of the related references, Section 3 describes the analytical method and the research procedure, and Section 4 provides the empirical results and discussion. Section 5 summarizes the study and presents the implications of the findings for policy.

2. Literature review

Pollution is generally regarded as damaging the quality of the environment. Porter and van der Linde [26] claim that environmental problems are not characterized by a waste of resources but refer to inefficiency in manufacturing productivity. Therefore, when an investment improves the degree of production effectiveness in the manufacturing processes as a whole, it can be called a GI [7]. Thus, GI is not limited to investments in renewable energy and energy efficiency, but can also include investing in the control of emissions from industry, the development of ecological infrastructure in urban areas, and the conservation of forests and grasslands.

Current research findings on GI and carbon emissions have led to the coexistence of two seemingly opposing views (positive and negative) to explain how GI affects carbon emissions [27]. In other words, GI is a double-edged sword that can increase as well as reduce CO2 emissions.

The detrimental effects of GI on CO2 emissions can be explained on the basis of the following research results. First, under the scale effect, GI will generally increase the level and scale of production [28], and the use of input materials in production, including natural resources and mineral energy will inevitably increase, thus generating more carbon emissions. Second, increased GI can be interpreted as increased economic activity, which implies the need for more energy-intensive products, resulting in higher CO2 emissions [29]. Third, GI may initially require the construction of appropriate supporting infrastructure, which will increase carbon emissions over time [30]. Finally, GI will likely lead to more energy consumption [31], which in turn will lead to increased long-term or short-term CO2 emissions [30].

By contrast, researchers have also found a positive correlation between GI and CO2 emissions. As one example, Abdouli and Hammami [32] show that GI leads to a higher level of economic development and increased per capita income, which in turn increases the demand for high-quality environmental and green developmental levels, thus reducing carbon emissions. Ye et al. [20] analyze the role GI can play in mitigating CO2 emissions and protecting the global ecosystem against degradation by promoting a shift in energy consumption away from high to low-emission energy products. Yang et al. [27] argue that GI can reduce carbon emissions through a "technology effect" mechanism, i.e., by improving the efficiency of production capacity and equipment through technological progress, which in turn can curb carbon emissions. Jiemin and Chen [30] show that increased investment in green energy is beneficial to improve the environment and decreasing CO2 emissions in the long term.

From the above discussion, it is clear that there is no linear relationship between GI and CO2 emission, but rather a more complex one. Both of those divergent views are supported to some extent by empirical evidence, and we consider both views by presenting a curvilinear relationship between GI and carbon emissions. At lower GI developmental stages, the harmful consequences of GI predominate, while at higher GI developmental stages, the beneficial consequences of GI become more pronounced. This study proposes that the initial stages of GI may be associated with scale effects and energy consumption, which increases carbon emissions, until it reaches a critical point at which the impact of GI on reducing CO2 emission becomes visible and GI has a positive impact that outweighs the negative impact, achieving a reduction in CO2 emission. Thus, there exists a graph showing the correlation between GI and CO2 emission, which follows the shape of an inverted U.

However, carbon emission reductions are often influenced by factors other than GI. Notably, Wang et al. [33] reveal that per capita carbon emissions are impacted by various factors, including per capita income, human capital, renewable energy consumption, natural resource rents, and trade openness. Similarly, Li et al. [34] demonstrate that carbon emissions are affected differently across income groups categorized as high, middle, and low, influenced by urbanization, economic structure, and trade structure. Specifically, as urbanization rates rise, the positive correlation between the economy and carbon emissions strengthens [35], while the relationship between renewable energy and the ecological footprint exhibits a non-linear pattern, initially decreasing and then increasing [36]. These findings underscore the significance of considering regional urbanization rates in carbon emission-related research. Moreover, Li et al. [37] highlight that the inhibitory effect of energy efficiency on carbon emissions in the transportation sector intensifies with higher energy efficiency. Additionally, income growth, private car usage, and cargo turnover play non-linear roles in contributing to carbon emissions. Wang et al. [38] further demonstrate that increasing trade openness leads to elevated carbon emissions at low to moderate levels, but a decrease in emissions at high levels. The non-linear effect of trade openness extends to economic growth and water consumption, providing novel insights for further consideration [39]. Additionally, the upgrading of industrial structure is found to play a significant role in the interplay between green finance and carbon emissions [40]. Consequently, this study posits that the role of green investment in shaping carbon emissions is not only characterized by a possible inverted U-shaped pattern but is also influenced by other factors, thereby exhibiting non-linear qualities.

Further, inspired by the discoveries of Song et al. [24] and Yang et al. [5], our results suggest that the effect of GI on CO2 emissions may in fact be distinct in China's regions in the west, center, and east. The related literature provides us with a series of variables that may affect GI and CO2 emissions, such as human capital, economic development, urbanization, and industrial structure. Considering the development differences among these three regions of China, we finally selected the regions' respective manufacturing structures and stages of socio-economic progress as the key factors. The remaining potential influences will be an important area for future research. Economic growth is a prerequisite for the effectiveness of environmental regulations, as shown by Wang et al. [41]. As the gross domestic product increases, the influence of the regulatory environment on the GI is shifting from being negative to being positive. Therefore, in more economically developed regions, the soundness of environmental institutions and regulatory systems has a remarkable positive influence on green production and support for the advancement of environmentally friendly production systems [42]. The impact of the GI on the reduction of pollution and the saving of energy will be more pronounced, thus reducing carbon emissions. By contrast, in lower-developed regions, governments will place greater emphasis to promote the economy and therefore give less attention to ecological development, and the effect of GI on CO2 may no longer be significant. Furthermore, the impact of GI may also be influenced by the industrial structure of the region. Wang and Wang [43] show that the relationship between industrial structure and GI varies across China's western, central, and eastern regions and that these differences reflect a state of imbalance. Wu et al. [44] also found noticeable regional differences in China's industrial structure. This regional heterogeneity will not only have an impact on GI but also affects carbon emissions. As the tertiary sector is characterized by low energy dependence and low pollution, upgrading the industrial structure to the tertiary level can significantly lower carbon emissions [45]. Consequently, this study takes into account the diversity in terms of both economic levels and manufacturing structures when examining the effects of GI on CO2 emission.

3. Methodology and data collection

3.1. Econometric model

To understand the impact of GI in relation to CO2 emission intensity, we treat all variables in the logarithmic form to eliminate heteroskedasticity and consider the following benchmark econometric model:

$$ln\ CO_{it} = \alpha_i + \beta_1\ ln\ GI_{it} + \gamma X_{it} + \lambda_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where CO_{it} is the dependent variable, defined as the intensity of CO2 emissions of province i in year t. GI_{it} is the core explanatory variable, indicating GI in province i in year t; The coefficients reflect the impact of the GI on the intensity of the CO2 emissions. X_{it} is the set of control variables at the level of the province over time, including infrastructure, demographic factors, technological factors, trade factors, and foreign direct investment. λ_i is the province-fixed effect, reflecting cross-province differences in the determinants of GI at a given time. λ_t provides the fixed effect of the year, and ε_{it} provides a random error term.

Application of Eq. (1), we can look at the existing link between GI and CO2 emitted intensity, taking the heterogeneous effect of the regional development level (GDP) and its industrial structure (IS) into account. To this end, we consider the following equations:

$$ln\ CO_{it} = \alpha_i + \beta_1\ ln\ GI_{it} + \beta_2[ln\ GI_{it} \times ln\ GDP_{it}] + \gamma X_{it} + \lambda_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$ln\ CO_{it} = \alpha_i + \beta_3\ ln\ GI_{it} + \beta_4[ln\ GI_{it} \times ln\ IS_{it}] + \gamma X_{it} + \lambda_i + \lambda_t + \varepsilon_{it} \quad (3)$$

where $\ln GI_{it} \times \ln GDP_{it}$ is the interaction term between GI and the level of economic development. This evidence suggests that the influence of GI on CO2 emissions intensity varies with GDP if the coefficient of this interaction term appears to be significant. In Eq. (2), the influence of GI depends in a linear form on GDP. Here we assume that β_2 is positive, suggesting that the extent of the overall influence of GI on CO2 emission in the provinces with a high level of GDP is greater. The same is true for $\ln GI_{it} \times \ln IS_{it}$ in Eq. (3) and its related interpretations.

However, the above methods are only able to test whether economic development and industrial structure affect the relationship between GI and carbon emissions, but are unable to measure the mechanism of this effect is. In this regard, some scholars have introduced dummy variables based on the above equation [46,47]. Dummy variables enable the delineation of provinces with different levels of economic and industrial structure, and further explore the response mechanism of GI to carbon emission under the condition of heterogeneity. The GDP of different provinces can be rationalized by taking the median, for example. But we take into account the fact that the data results for the level of industrial structure in each province are very close to each other. The method of dividing the data using only the median or other ways, and marking a province as having a high or low level of industrial structure is not rigorous. So, this paper does not consider the introduction of dummy variables to analyze the above impact mechanisms.

Additionally, assuming that we do find a suitable method to classify the level of industrial structure, the above methods still have flaws. For example, the construction of interaction terms relies on a priori information, which may not accurately measure the heterogeneity effects of economic development and industry structure, or even lead to biased estimates [48]. More importantly, Eq. (1) to Eq. (3) represent linear assumptions about the impact of GI and are likely to suffer from specification errors. In practice, the impact of GI will not follow a strictly linear pattern as assumed. To overcome this problem, a PLFC model is introduced in this study. This empirical model is flexible enough that it not only avoids estimation bias but also provides a better measure of heterogeneity in different regions. The specific model is shown below:

$$\ln CO_{it} = g(\ln GDP_{it})\ln GI_{it} + \gamma X_{it} + \lambda_i + \lambda_t + \varepsilon_{it} \tag{4}$$

$$\ln CO_{it} = g(ln\ UB_{it})\ln GI_{it} + \gamma X_{it} + \lambda_i + \lambda_t + \varepsilon_{it} \tag{5}$$

Eq. (4) is split into two separate components: the nonlinear part $g(\ln GDP_{it})$ and the linear part γX_{it}. $g(\ln GDP_{it})$ captures the heterogeneous effect of GI on the variation of the emissions intensity of CO2, which is an unknown function of variable $\ln GDP_{it}$. Eq. (5) is similarly interpreted. The rest of the definitions of the parameters are consistent with Eq. (1). In this study, we estimate Eq. (4) and Eq. (5) using the sieving method. See Du et al. [49] and Zhang and Zhou [50] for more details on the modeling procedures.

3.2. Variables and data

Balanced panel data over the period 2003 to 2020 covering 30 provinces in China are collected in this study. The variables are constructed as mentioned below.

3.2.1. Dependent variable

In accordance with the latest available research, including Abban et al. [51], Ali et al. [52], and Mo [53], to measure CO2 emissions, this study uses the intensity of CO2 emissions as a proxy measure and a dependent variable. The formula for calculating carbon emission intensity is " CO_2 emissions/GDP," indicating the carbon dioxide emissions (tons) generated to create 10,000 Yuan in GDP, i.e., the cost of producing 10,000 Yuan of GDP to environmental quality. With Shan et al. [54] and Shan et al. [55] on CO2 emissions measurement methods, this study calculates the provincial CO_2 emissions of China on the basis of 'apparent emissions consumption' and up-to-date emission factors. The CO2 emissions associated with fossil fuels are estimated for each type of energy. If AD_i is the activity data of the ith fossil fuel burned within the provincial area and EF_i is the emission factors of the related ith fossil fuel, the total CO_2 emissions (CE) of a province can be obtained by summing up the carbon emissions of different energy types, as shown in Eq. (6):

$$CE = \sum AD_i \times EF_i \tag{6}$$

3.2.2. Independent variable

GI has been identified as the core explanatory variable. Shen et al. [7] argue that GI is any capital investment that has the potential to be an overall improvement in the efficiency of the manufacturing processes. Therefore, the scope of GI is not limited to green and clean energy investments, but it is a much broader concept. This study defines GI on the basis of the explanations of Li et al. [4] and Yilanci et al. [56], which define GI as the total amount invested in the area of energy saving and environmental protection. Specifically, GI is the aggregate of investing in the prevention of atmospheric emissions from industry, the construction of infrastructure to protect the environment in urban areas, water conservation facilities, and forestry and grass protection.

3.2.3. Control variables

After reviewing the corresponding studies, the control variables were identified as the following: (1) Infrastructure: we use regional traffic density, measured by average ratio of the total miles of regional roads and railways to the total area of the region, to reflect the development level of infrastructure; (2) Population factor: Population density is used as a proxy for population factor and is expressed in the density of the population per unit of area of the region; (3) Technology factor: It is calculated by expressing the share of R&D investment expenditure in GDP of the region; (4) Trade factor: It is computed as a proportion of the region's GDP accounted for by regional trade in goods imported and exported; (5) FDI (Foreign Direct Investment): This refers to the actual amount of foreign investment entering the region. Data for some of the control variables had a few missing values at the provincial level, which have been extended in this study by linear interpolation, further, all data have been logarithmically transformed to control for the impact of heteroscedasticity.

3.2.4. Variables introduced when exploring regional heterogeneity

Concerning Tahir et al. [57], Tong et al. [42], and Wu et al. [44], economic development level (GDP) and industrial structure (IS) are introduced to investigate the heterogeneity of the effects of GI on CO2 emissions from region to region. To indicate regional economic performance, GDP per capita is employed in this study. Referring to Wu et al. (2021), to reflect the process of industrial structure upgrading comprehensively, the present work constructs the index for measuring the diversification of industrial structure. The index construction method is shown in Eq. (7):

$$indication = \sum_{i=1}^{3} x_i \times i, 1 \leq indication \leq 3 \tag{7}$$

where x_i denotes the portion of the output of industry i in the total output, indicating the upgrading status of the industry among the three types of industries.

3.3. Data sources and description

For the analysis, we collected comprehensive panel data from 2003 to 2020 covering 30 Chinese provinces. Tibet has traditionally been excluded from China's reported energy statistics due to its small-scale industrial development and low level of energy consumption. Therefore, Tibet has not been selected as part of the statistical sample for the present research. In addition, the statistical sample does not cover Hong Kong, Macao, and Taiwan on account of the lack of availability of relevant data.

The provincial carbon emission data were mainly collected through the CEADs dataset. For the data lacking in CEADs, we used Eq. (2) to calculate carbon emissions according to the energy data and CO2 emissions factors of each province published in China Energy Statistical Yearbook. The GI of each province is relatively scattered, and the source of the data used for the present paper was obtained from the China Statistical Yearbook and the China Environmental Statistical Yearbook. The data for the control variables have been collected through the EPS data platform and various other statistical yearbooks. Figures on GDP and industrial structure are taken from the Chinese Yearbook of Statistics and the Chinese Regional Economic Statistical Yearbook, respectively.

4. Empirical results

4.1. Descriptive statistics

In any study with a large data set, descriptive statistics can help researchers manage the data [58]. The results of the descriptive analyses of the relevant parameters, such as the intensity of CO2 emissions and the GI, are presented in Table 1. The logarithmic mean of the intensity of CO2 emission is 0.6908, the minimum is 1.6264, and the maximum is 2.5894. For GI, the logarithmic mean value is 5.4254, the minimum is 2.2671, and the maximum is 7.3662.

4.2. Multiple regression analysis

We transformed the raw data into natural logarithms to resolve dimensional differences and potential heteroskedasticity between variables. The regression analysis of GI on the intensity of CO2 emissions is presented in Table 2. Excluding the control variables, column (1) shows a coefficient of −0.0696 for GI, i.e., this value turns out to be statistically significantly and negatively correlated with GI at the 5% level, indicating that GI can reduce carbon emission intensity. Column (3) still has a statistically significant negative coefficient for GI after including the control variables, suggesting that GI can reduce CO2 emissions in China and the relationship is influenced by infrastructure, demographic factors, technological factors, and foreign direct investment. In contrast to the study by Li

Table 1
Descriptive statistical characteristics of variables.

Variable	n	Mean	SD	Minimum	Maximum
lnCO	540	0.6908	0.7651	1.6264	2.5894
lnGI	540	5.4254	1.0359	2.2671	7.3662
lnBF	540	8.7701	0.8430	5.8657	10.0103
lnPF	540	5.4379	1.2715	2.0002	8.2813
lnTEF	540	6.9128	0.8095	8.8242	4.8289
lnTF	540	−1.7136	0.9872	−4.8832	0.5834
lnFDI	540	5.2642	1.6802	−1.2203	7.7219
lnGDP	540	9.3253	1.0698	5.9532	11.6151
IS	540	2.3246	0.1358	2.0276	2.8360

Note: CO: carbon emission intensity, GI: green investment, BF: infrastructure, PF: population factor, TEF: technology factor, TF: trade factor, GDP: per capita gross domestic product, FDI: foreign direct investment, IS: industrial structure upgrading index.

Table 2
Impact of GI on carbon emission intensity.

Variable	CO(1)	CO(2)	CO(3)	CO(4)
GI	−0.0696** (−2.28)	0.4783*** (4.81)	−0.0618** (−2.09)	0.3746*** (3.81)
GI2		−0.0503*** (−5.77)		−0.0405*** (−4.64)
BF			−0.3778*** (−4.64)	−0.3945*** (−4.94)
PF			−1.0675*** (−5.45)	−0.9930*** (−5.15)
TEF			0. 1508*** (3.75)	0.1241*** (3.11)
TF			−0.0019 (−0.05)	0.0231 (0.65)
FDI			−0.0683*** (−3.93)	−0.0564*** (−3.28)
The year effect	Yes	Yes	Yes	Yes
The regional effect	Yes	Yes	Yes	Yes
Constant	1.4878*** (11.10)	0.0975 (0.36)	11.6196*** (7.69)	10.0535*** (6.62)
R2	0.7221	0.7398	0.7576	0.7679
Obs	540	540	540	540

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The numbers in indicate the t-values of the relevant statistics. CO: carbon emission intensity, GI: green investment, BF: infrastructure, PF: population factor, TEF: technology factor, TF: trade factor, FDI: foreign direct investment.

et al. [4], it was found that GI can significantly reduce carbon emissions in both the short and long term. This paper focuses on examining the nonlinear effects of the scale of development of GI. In response, Column (2) adds the quadratic term of GI and the coefficient is −0.0503, which is negative considering a significance of 1%. The results show that the relation of GI to CO2 emissions has the characteristic of an inverted "U", i.e., when GI reaches a certain level, its emission reduction effect gradually comes into play. Column (4) considers the effect of control variables based on Column (2), and the coefficient of the square of the GI term is still in a significant negative position showing an inverted U-shaped curve, and the control variables that influence carbon emissions are consistent with those in Column (3). One possible explanation is that GI in industries which are in the early stages of development may demand more input from factors of production such as natural resources and mineral energy. At the same time, the initial construction may require corresponding supporting infrastructure, which allows many energy-intensive products to be consumed, thus increasing carbon emissions. This is consistent with the current view of related research [59]. When GI reaches a certain level, the demand for a high-quality environment and green development will increase, and the efficiency of production capacity and equipment will be enhanced by technological advancement [60]. The energy-saving and emissions mitigation effects of GI come into play, and GI has a positive impact that outweighs the negative impact, achieving a reduction in carbon emissions.

4.3. Heterogeneity analysis

Given the heterogeneous effects of social and economic environments of different regions on the regression results, we further examined the effects of GI on carbon emission intensity in the region of eastern, central, and western. The evaluation of heterogeneity is shown in Table 3. The results in columns (1) (3) (5) show that the GI is negative in the Western and Central regions at the 5% and 10% levels of significance respectively, whereas in the Eastern region, the coefficient is insignificant. This indicates that the Chinese

Table 3
Heterogeneity analysis results.

Variable	Eastern Region		Central Region		Western Region	
	CO(1)	CO(2)	CO(3)	CO(4)	CO(5)	CO(6)
GI	0.0158 (0.44)	0.9170*** (9.89)	−0.2342** (−2.40)	−0.4671 (−1.03)	−0.1093* (−1.83)	−0.5997*** (−2.83)
GI2		−0.0848*** (−10.20)		0.0207 (0.52)		0.0432** (2.41)
BF	−0.4379*** (−3.62)	−0.2294** (−2.36)	−0.5203* (−1.94)	−0.5652** (−2.00)	−0.3868*** (−2.86)	−0.3051** (−2.22)
PF	−1.2161*** (−4.54)	−1.2435*** (−5.92)	1.4983** (2.00)	1.5153** (2.01)	0.7299 (1.44)	0.7092 (1.42)
TEF	0.2464*** (3.33)	0.2090*** (3.59)	0.1672 (1.62)	0.1532 (1.43)	0.0885 (1.54)	0.1420** (2.33)
TF	0.3697*** (3.73)	0.2853*** (3.65)	−0.1721* (−1.89)	−0.1725* (−1.88)	−0.0451 (−0.95)	−0.0695 (−1.45)
FDI	−0.1020*** (−2.69)	−0.1014*** (−3.41)	−0.1537*** (−3.33)	−0.1583*** (−3.36)	−0.0137 (−0.58)	−0.0369 (−1.47)
The year effect	Yes	Yes	Yes	Yes	Yes	Yes
The regional effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	14.7517*** (6.34)	10.5205*** (5.62)	−0.3284 (−0.07)	0.4700 (0.10)	2.2003 (0.74)	3.3475 (1.13)
R2	0.8402	0.9024	0.7702	0.7708	0.7725	0.7804
Obs	198	198	144	144	198	198

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The numbers in indicate the t-values of the relevant statistics. GI: green investment, BF: infrastructure, PF: population factor, TEF: technology factor, TF: trade factor, FDI: foreign direct investment.

western and central regions, which have a relatively low industrial structure level and are at a resource-intensive stage of economic growth. These regions have a relatively high CO2 emission intensity and more scope for GI. In the eastern region where economic and technological development levels are higher, the inhibiting function of GI on carbon emission intensity may have been exerted earlier, and the results are no longer significant.

The study findings on the primary term of GI align with the existing literature [40]. However, the existing literature has not yet explored the nonlinear effects associated with the introduction of a secondary term of GI. In order to address this research gap, the present paper incorporates the quadratic term of GI into the regression analysis, as depicted in Columns (2) (4) (6). The regression coefficient of the quadratic term of GI in the eastern region is −0. 0848, which is negative considering a significance of 1%. The results show that the relation of GI to CO2 emissions has the characteristic of an inverted "U", consistent with the total effect. This indicates that when GI reaches a certain level, its emission reduction effect gradually comes into play. The non-linear effect of GI in the central region is not significant, suggesting that we should focus on the abatement effect of its primary term. This also motivates us to continue to investigate how the nonlinear effects of GI change with the inclusion of covariates. The regression coefficient of the quadratic term for the western region is 0.0432, which is positive considering a significance of 5%. This unexpected result suggests a U-shaped effect of GI, which is contrary to the overall effect. One possible explanation for this discrepancy is the heavy reliance of the western region on local industries [61]. Excessive GI imposes substantial environmental demands on these industries, leading to resource crowding out and depletion. For instance, in the pursuit of meeting carbon emission targets, enterprises may engage in research and development activities that generate additional carbon emissions. Moreover, they may opt for inexpensive raw materials with high carbon content to offset the high costs associated with research and development, consequently increasing carbon emissions.

4.4. *Estimation results of the PLFC model*

The existence of heterogeneity from region to region in the influence of GI on CO2 emissions has already been demonstrated in section 4.3. In this section, we further consider whether this heterogeneous effect originates from different levels of the economy. The development of GI is a long-term process, during which the marginal effect of GI on carbon emissions will change and show non-linear characteristics. Considering this, the study uses a PLFC model for testing. Table 4 estimates the heterogeneous effect model, with Columns (1) to (3) considering the effect of the GDP and Columns (4) to (6) considering the effect of industrial structure.

We first introduced an interaction between GI and GDP per capita using a traditional parametric panel data analysis to enable direct comparisons. In column (1) of Table 4, control variables are not added and the interaction term shows a significant negative value at the 1% level, suggesting that the effects of GI on CO2 emissions intensity are constrained by GDP. The coefficient on the interaction term is still found to be significantly negative at 1% level when controlling for variables (see column (2)). In Column (3), we report the estimation outcomes of the PLFC model's linear part, which generally align with the conventional model. The estimation of the non-parametric part of g(·) is displayed in Fig. 1.

Fig. 1 can be subdivided into three parts. Specifically, when $\ln GDP_{it} \leq 8.95$, The impacts of GI on the intensity of CO2 emission appear to be substantially positive. When $8.95 < \ln GDP_{it} < 9.70$, there seems to be no substantial effect of GI on the intensity of CO2 emissions. When $\ln GDP_{it} \geq 9.70$, the contribution of GI to CO2 emissions intensity has a significantly negative effect. This means that GI can help to lower CO2 emissions only when the GDP is above a specific value, while below this specific value, GI may even increase carbon emissions. Wang et al. [41] investigated the impact of economic development on environmental regulation through a PLFC model. The study finds that as GDP increases, the impact of environmental regulations on green productivity changes from negative to

Table 4
Results of the estimation of heterogeneous effects models.

Variable	CO(1)	CO(2)	CO(3)	CO(4)	CO(5)	CO(6)
GI	0.8021*** (10.14)	0.6955*** (8.21)		0.4611*** (3.93)	0.2575** (2.04)	
GI × GDP	−0.0865*** (−11.72)	−0.0763*** (−9.44)				
GI × IS				−0.2416*** (−4.68)	−0.1435*** (−2.59)	
BF		−0.3193*** (−4.25)	−0.0708* (−1.94)		−0.3762*** (−4.65)	−0.1376*** (−3.76)
PF		−0.7257*** (−3.94)	−0.1345 (−0.60)		−0.8383*** (−3.92)	−0.5379*** (−3.03)
TEF		0.0760** (2.00)	0.0879*** (3.00)		0.1368*** (3.39)	0.0881*** (2.80)
TF		0.0315 (0.94)	0.0160 (0.73)		0.0091 (0.25)	−0.0053 (−0.20)
FDI		−0.0195 (−1.16)	−0.0219* (−1.74)		−0.0630*** (−3.62)	−0.0500*** (−3.09)
The year effect	Yes	Yes	Yes	Yes	Yes	Yes
The regional effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.8118*** (6.16)	8.0732*** (5.61)		1.5338*** (11.65)	10.2797*** (6.47)	
Obs	540	540	510	540	540	510

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Columns (3) and (6) show the linear part of the partial linear functional coefficient model results. CO: carbon emission intensity, GI: green investment, BF: infrastructure, PF: population factor, TEF: technology factor, TF: trade factor, GDP: gross domestic product, FDI: foreign direct investment, IS: industrial structure.

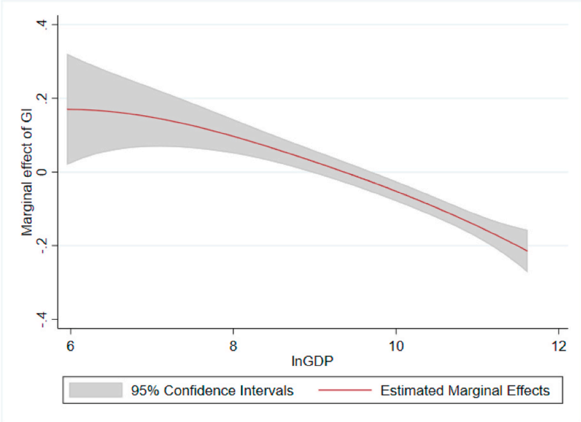

Fig. 1. Estimates of the marginal effect of GI on CO2 emission intensity in relation to GDP.
Note: The red curve indicates the estimated unknown function g(•). The gray shaded area corresponds to the 95% confidence interval.

positive, thereby reducing carbon emissions. This is consistent with the findings of this paper. Notably, when $\ln GDP_{it}$ <8.95, the marginal effect of GI decreases as GDP increases. When $\ln GDP_{it}$ >9.70, the marginal effect of GI increases as the GDP rises. The overall trend of change in the marginal utility of GI shows that enhancing the economic development of a region contributes to reducing its CO2 emissions.

Next, we have studied the role played by the sectoral composition of GI in terms of its potential to reduce emissions. First, an interaction between GI and industrial structure upgrading index was introduced. Column (4) of Table 4, reveals the interaction term to be significant at 1% with the control variables not added. The coefficient on the interaction term continues to be negative at the 1% significance in column (5) with the control variables added. This indicates that industrial structure significantly affects the emission reduction effect of GI. The results of the estimation of the PLFC model's linear part are displayed in column (6), which remain largely consistent with the findings of the conventional model. The estimation of the non-parametric section of g(·) are illustrated in Fig. 2.

Fig. 2 can be split essentially into two distinct components. Specifically, GI on the intensity of CO2 emissions is not significant when IS $\leq$ 2.07. When IS > 2.07, the influence of the GI on the intensity of CO2 emissions has a significant negative effect. This implies that the emissions reduction effects of GI can be significantly exploited after the industrial structure upgrading index exceeds a threshold value. The variation in the marginal effect of GI when IS > 2.07 further subdivides Fig. 2 into two parts. The marginal effect of GI decreases when 2.07<IS < 2.18. By continuously optimizing the structure of the industry, the marginal effect of GI increases with the increasing index of industrial structure upgrading when IS $\geq$ 2.18. Thus, the marginal effect of GI may not have significance when IS exceeds the threshold value of 2.07. Only after IS crosses the critical inflection point of 2.18, the marginal effect of GI will keep increasing and more targeted at cutting CO2 emissions. Few articles have been written to quantitatively determine the impact of changes in industrial structure on carbon emissions, and the results of this paper provide new ideas for research in this area.

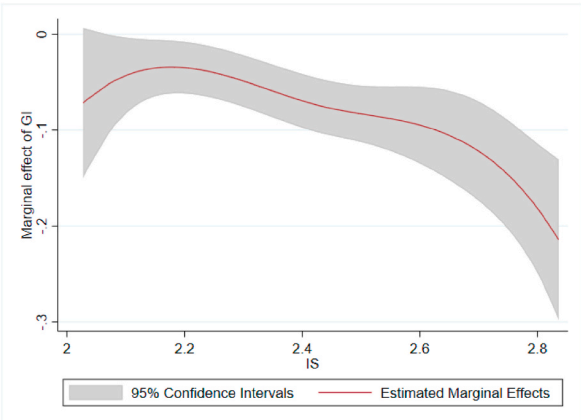

Fig. 2. Estimated findings of the marginal effect of GI on CO2 emissions intensity by industrial structure
Note: The red curve indicates the estimated unknown function g(•). The gray shaded area corresponds to the 95% confidence interval.

Table 5
Robustness tests.

	Alternative explained variable (1)	Alternative explanatory variable (2)	Lags one period (3)	Lagging Phase II (4)	Instrumental variable method (5)	Sample replacement (6)	Adding control variables (7)
GI	0.7763*** (8.11)	0.1664* (1.91)	0.2981*** (2.95)	0.1032 (0.98)	0.4191** [2.41]	0.3893*** (4.06)	0.2435** (2.37)
GI2	−0.0617*** (−7.36)	−0.0240*** (−2.89)	−0.0352*** (−3.90)	−0.0195** (−2.11)	−0.0480*** [-3.20]	−0.0453*** (−5.29)	−0.0260*** (−2.83)
BF	−0.1034 (−1.35)	−0.3898*** (−4.84)	−0.4246*** (−5.11)	−0.3480*** (−4.07)	−0.4158*** [-3.17]	−0.5184*** (−6.07)	−0.1927** (−2.40)
PF	−1.5427*** (−8.33)	−1.1285*** (−5.81)	−1.0498*** (−4.89)	−1.0358*** (−4.60)	−0.9825*** [-4.89]	0.4029 (1.51)	−0.6955*** (−3.74)
TEF	0.0644* (1.68)	0.1438*** (3.60)	0.0506 (1.21)	0.0551 (1.26)	0.1163*** [2.77]	0.0576 (1.45)	0.0668* (1.72)
TF	−0.0301 (−0.88)	0.0144 (0.40)	−0.0318 (−0.83)	−0.1048** (−2.58)	0.0376 [0.97]	0.0587 (1.56)	−0.0178 (−0.52)
FDI	0.0122 (0.74)	−0.0664*** (−3.86)	−0.0590*** (−3.27)	−0.0561*** (−2.98)	−0.0532*** [-3.10]	−0.0225 (−1.30)	−0.0433*** (−2.61)
GOV							0.5792*** (6.10)
ES							0.0105 (0.73)
CB							−1.2277*** (−3.14)
The year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
The regional effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	8.5650*** (5.87)	11.4737*** (7.68)	10.1714*** (6.08)	9.8924*** (5.56)	10.3633*** [5.36]	3.12369* (1.74)	10.3065*** (6.27)
R2	0.7463	0.7631	0.7534	0.7366	0.9416	0.7581	0.7972
Obs	540	540	510	480	510	468	540

Note. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The numbers in denote the z-values of the relevant statistics, and the numbers in denote the z-values of the relevant statistics. GI: green investment, BF: infrastructure, PF: population factor, TEF: technology factor, TF: trade factor, FDI: foreign direct investment, GOV: government regulation, ES: energy structure, CB: consumer behavior

4.5. Robustness tests

4.5.1. Endogeneity test

Carbon risk and green risk are mainly measured by carbon emissions. Carbon emission intensity has been included in the evaluation system of investment or capital, and carbon-related risk can be an important factor affecting GI. Further, considering the possible two-way causality problem in the underlying regressions, to minimize the disturbance caused by such problems, this study regresses the GI and the quadratic term of GI with the control variables lagged-period and lagged two periods, respectively. Columns (3) and (4) of Table 5 clearly depict that there continues to be an inverted U-shaped graph between the lagged order of GI and the intensity of CO2 emissions. In terms of the positive and negative properties of coefficient values and the significance of the lagged effect estimation results, the estimation results remain robust and provide preliminary evidence that the basic statements contained in the present paper are robust. To further alleviate the estimation bias related to the endogeneity of variables, and considering the temporal correlation and path dependence of GI in a region in different years, the first-order lagged value of GI is chosen as the instrumental variable. The estimation of instrumental variables is reported in column (5) of Table 5, where the effect of GI on the intensity of CO2 emission remains significant and consistent with the evidence in the above section, which again confirms the reliability of the statements.

4.5.2. Other robustness tests

Considering the problem of possible measurement bias of the explanatory variables, carbon emission per capita is selected as a replacement variable for the intensity of CO2 in this research. The specific outcomes are summarized under Column (1) in Table 5., where the relationship between the replaced CO2 emission variables and GI remains significant and in line with historical findings. Additionally, considering that there is still a bias in the definition of GI in academia, some academics consider GI to be an investment in reducing CO2 emissions, the definition of GI is narrowed in this study so that it is equal to the sum of investments in the construction of water facilities and conservation of forestry, grasses, and trees. The specific outcomes are available in column (2) in Table 5, where the relationship between the replaced GI variables and the intensity of CO2 emission remains in line with the estimates received from the previously used measures. Besides, considering that municipalities directly controlled by the Central Government are situated exactly in the same places as provinces, the four municipalities are excluded from this study due to their unique economic characteristics and political status. Column (6) of Table 5 reports the outcomes after replacing the sample and the conclusions still hold. Considering further, factors such as the adoption of renewable resources, government regulations, and consumer behavior may have an impact on carbon emissions. In this regard, this paper adds renewable energy adoption (ES: share of natural gas consumption), government regulations (GOV: ratio of government fiscal expenditure to GDP), and consumer behavior (CB: years of education per capita) as new control variables to the original equation for regression. As shown in column (7), the coefficients and significance of GI remain robust after adding new control variables. All the above tests prove the reliability of the research results.

5. Conclusions, policy implications and limitations

5.1. Conclusion

It remains unknown what factors will govern the impact of GI on carbon emissions. For this reason, the present article prioritizes the examination of benchmark relationship and regional heterogeneity between GI and CO2 emissions using a panel dataset covering 30 Chinese provinces. Furthermore, this study relaxes the linearity assumption of traditional studies by introducing a PLFC panel data model. The model provides some novel results by considering the heterogeneous effects of regional GDP and industrial structure. The main findings of this paper are as follows.

(1) The results show that GI makes a significant contribution to reducing carbon emissions. Introducing the GI quadratic term for regression, we can see that the graph showing the relationship between GI and CO2 emissions is an inverted U-shape, i.e., when the scale of GI reaches a certain level, its emission reduction effect gradually comes into play. This finding suggests that the initial stages of GI development were characterized by disorganization and inefficiency, driven primarily by market forces.

(2) When considering regional heterogeneity, we introduce the quadratic term for GI, and the results confirm the inverted U-shaped relationship in the eastern region, the lack of significance in the central region, and a U-shaped relationship in the western region. However, the exact cause of the U-shaped relationship in the west remains uncertain. We speculate that this may be due to resource crowding resulting from excessive GI. Therefore, investigating the impact of GI in the western region is an important direction for future research.

(3) The analysis reveals that the effectiveness of GI in reducing emissions is contingent upon the economic performance and industrial structure of the region. Only when the GDP surpasses a certain threshold does GI begin to play a role in reducing carbon emissions. Additionally, the industrial structure of a particular area determines the impact of GI on emissions limitation. It is only when the index of industrial structure upgrading reaches a critical point that the effect of GI on reducing CO2 emissions becomes significant. Furthermore, the marginal effect of GI is enhanced by continuous improvements in the industry's structure after reaching an important turning point.

5.2. Policy implications

According to the aforementioned evidence, we offer targeted suggestions for policy action to improve the design of government mechanisms for the limitation of CO2 emissions.

(1) The empirical evidence shows that GI has effectively reduced CO2 emissions in China, and the emission effectiveness of GI will be better exerted with the development and improvement of GI in the long term. Consequently, policymakers should design policies that encourage GI. The provision of tax rebates for investments in environmentally friendly projects can be considered a creditable political action. Further, the fact that GI may not have significant effects or may even have negative effects in the short term should not be a reason for governments to discard GI projects. In response to GI, until the inverted U-shaped inflection point occurs, governments should focus on the pressures of green R&D costs and fees, and take the risk of potentially increasing carbon emissions; After the emergence of the inverted U-shaped inflection point, the Government should expand the favorable effects brought by GI and focus on the market benefits of green economic development. Certainly, at the early stage of the development of GI, we also need to guard against "campaign carbon reduction" (an excessive, blind behavior that refers to unrealistic carbon reduction beyond the current stage of development), which is an undesirable phenomenon that has recently emerged. This is a recent phenomenon.
(2) The impact of GI on CO2 reduction varies across the western, eastern, and central regions of China. In the eastern region, it is important to remain committed to the implementation of GI policies and have confidence in their effectiveness and superiority. For the western and central regions, which are in the early stages of economic development and have high resource consumption, policymakers should focus on designing a comprehensive environmental economic promotion ecosystem and actively promote the development of regional infrastructure to efficiently reduce carbon emissions. It is worth emphasizing that local governments in the western region should strike a balance between environmental, industrial, and economic development, avoiding a one-size-fits-all approach.
(3) The marginal effect of GI varies depending on the GDP and industrial structure. The government should encourage high-speed, high-quality economic construction, and the introduction of appropriate policies to accelerate regional growth in the western and central areas. Furthermore, the marginal effect of industrial modernization on the promotion of GI is increasing. However, the government should not blindly push for an expansion of the share of tertiary, but should optimize the industrial structure on the basis of rationalization, so that to maximize the effectiveness of GI in curbing emissions.

5.3. Further thinking and limitations

China's carbon emissions are influenced by various factors, including policy, culture, geography, and other contextual elements. Aspects of policy considerations, China has established a dual-carbon target for 2020 and has implemented energy-saving and emission-reduction policies and regulations, such as the Administrative Measures for Carbon Emission Trading (Enforcement) and the Opinions on Improving the Institutional Mechanisms and Policies and Measures for Green and Low-Carbon Transformation of Energy Sources. These efforts demonstrate China's unprecedented attention to carbon emission reduction, potentially enhancing the impact of GI on carbon reduction. Cultural factors also play a role, as the low-carbon awareness of the Chinese population has increased substantially in recent years, possibly due to government-led campaigns. Geographically, there are notable variations in economic development patterns, industrial structures, and technological advancements among China's three regions: East, Central, and West. The eastern region boasts a more advanced industrial structure, with manufacturing and service industries dominating and leading economic development. The central region, on the other hand, relies more on traditional industries such as heavy industry and agriculture. The western region's economic growth is primarily driven by the energy and mineral sectors, resulting in a relatively homogeneous industrial structure. These regional disparities significantly influence the research conclusions. Considering the unique factors specific to China, the findings of this study may not be directly applicable to the global context but can offer valuable insights for developing countries with similar circumstances. While this paper contributes new insights and conclusions to research in the Chinese context, it is crucial to explore the generalizability of these results through future studies. Understanding the transferability of these findings remains an important area for further research.

Furthermore, an in-depth examination of the U-shaped correlation between GI and carbon intensity in the western region lacks a scientific explanation, as previously mentioned. A comprehensive investigation focused specifically on the western provinces and cities will be conducted to address this knowledge gap. Additionally, apart from GDP and industrial structure, various other potential factors that may exert influence warrant further exploration. Building on existing literature, indicators like the level of urbanization will be incorporated into the research framework to enhance our holistic comprehension of the relationship between GI and carbon emissions. Moreover, it is important to note that the current study is constrained to the provincial level due to data collection challenges, neglecting the specific circumstances within individual provinces. However, considering the growing accessibility of data, future research can refine the study by including city-level analysis.

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Author contribution statement

Zhe Huang: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Data availability statement

Data will be made available on request.

Additional information

No additional information is available for this paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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