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Marginal effect of electricity generation on CO2 emissions: Disaggregated level evidence from China by KRLS method and high-frequency daily data

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ABSTRACT

The effect of energy use on carbon dioxide (CO_2) emissions has been frequently studied in the literature. These studies have mainly concluded that countries should decline (increase) the use of fossil fuel (clean) energy. However, the literature suffers from a significant shortcoming as it does not focus on the marginal effect of a 1 % increase for each energy generation source on sectoral CO_2 emissions. Therefore, a detailed analysis is conducted in this study to examine the relationship between electricity generation (EG) and CO_2 emissions at a disaggregated level. The focus is on China, the world's leading country in terms of CO_2 emissions and energy use. Thus, the study considers source-based EG and sector-based CO_2 emissions, uses high-frequency daily data between January 1, 2019, and December 31, 2022, and applies the kernel-based regularized least squares (KRLS) method. The outcomes show that (i) the effects of EG sources on sectoral CO_2 emissions follow a nonlinear structure, suggesting that the marginal effect varies by sector, EG sources, and estimation models (either incremental or degressive). Therefore, there are certain externalities among alternative EG sources for the effects of CO_2 emissions in the sectors; (ii) the statistically significant effects of EG sources on CO_2 emissions vary by sector and constructed models, showing that some EG sources are much more important for CO_2 emissions in some sectors. For this reason, not all EG sources have the same importance for sectoral CO_2 emissions; (iii) the KRLS method has a higher estimation ability of CO_2 emissions, reaching ~99.8 %, which provides novel outcomes and allows researchers to argue various policy options based on the obtained results. The study thus highlights varying marginal impacts of EG sources on sectoral CO_2 emissions. The changing marginal influence is a crucial point that should be considered by Chinese policymakers when formulating energy-related environmental policies.

1. Introduction

Climate change, which brings various problems such as air pollution, biodiversity decline, extreme weather events, and global warming, has a negative impact on societies and countries in the world. Due to the increasing adverse effects on humanity, recent studies have focused heavily on exploring the path to a carbon-neutral economy [1,2]. In this context, research is increasingly being conducted into the causes of high emissions and possible solutions to decline or completely curb CO_2 emissions to propose potentially beneficial measures [3,4].

According to recent data [5,6], CO_2 emissions are the largest contributor to all greenhouse gasses, and some countries (e.g., China, the US, and India, in that order) play a leading role in causing high CO_2 emissions. As a result, recent efforts have focused more on CO_2 emissions than on other types of emissions. Recent studies have often looked at the countries that have caused higher CO_2 emissions. In the literature, some studies have analyzed the global level (e.g., Ref. [7–13]), while some others have frequently treated the case of China as a leading emitting country (e.g., Ref. [14–18]).

For the empirical investigation, some studies have used low-frequency data (e.g., Ref. [19]), while a few studies have included high-frequency data (e.g., Ref. [20,21]) across different country groups.

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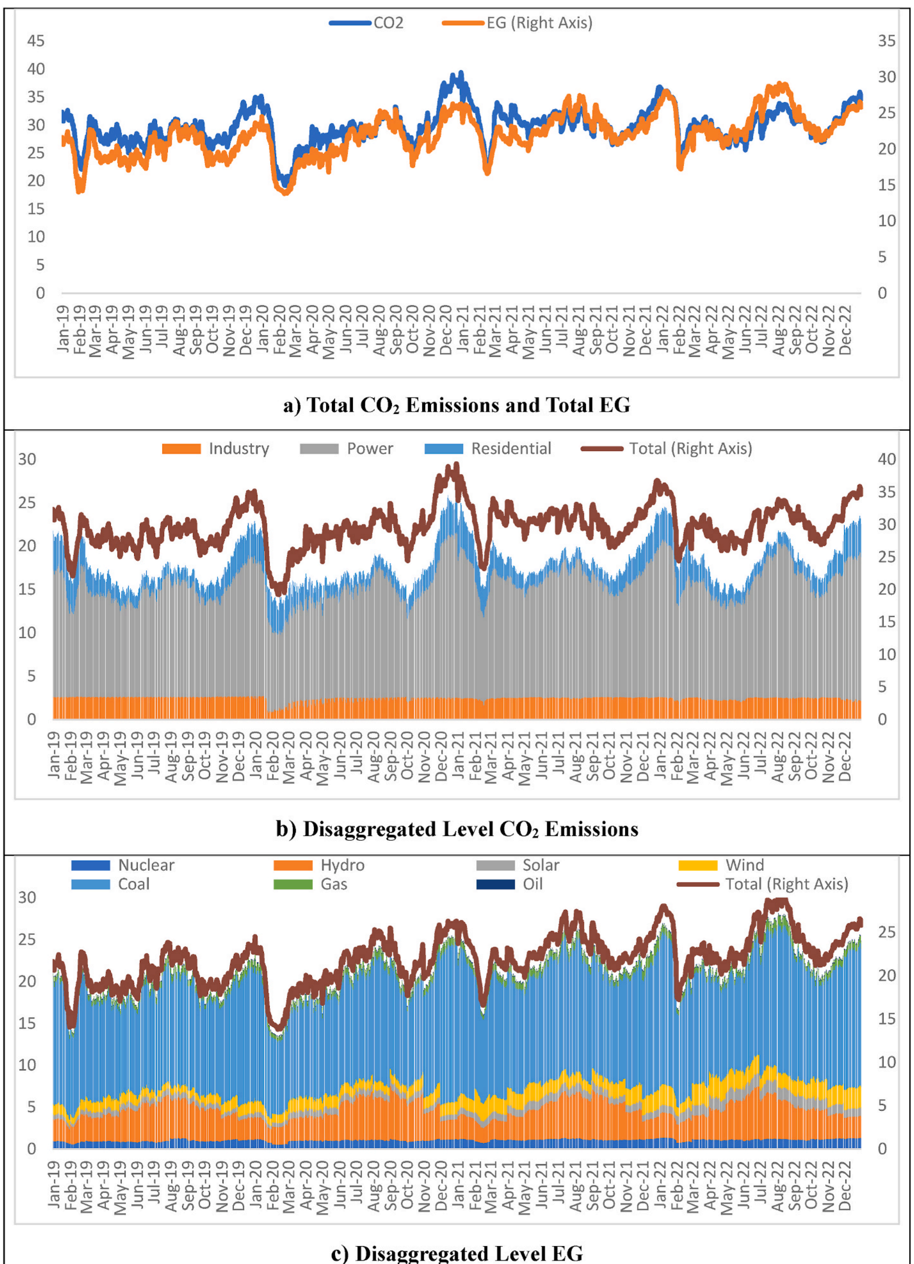
However, data frequency is highly effective in empirical modeling because low-frequency data are more interested in the overall condition over the years, while high-frequency data are more sensitive to dynamic changes over time [22]. Therefore, the use of high-frequency data is crucial for a much better estimation [23]. Another critical point is the use of disaggregated level data instead of the aggregated level to examine the underlying relationship, as it is most likely that there is a trade-off between the variables under consideration.

Previous studies have included a variety of factors in empirical analyses. According to recent data [5,6], energy consumption is the largest contributor to CO_2 emissions, renewable energy use is seen as an important alternative [24], and EG is a critical proxy for energy use. Looking at country cases, it is clear that China is again the leader in both high electricity use and CO_2 emissions. Fig. 1 presents the development of China's EG and CO_2 emissions.

In Fig. 1a, both the CO_2 emissions and the EG have changed over the days. The CO_2 emissions have a value between 19.22 and 39.39 $MtCO_2$/day, while the EG has a value between 13.81 and 29.14 TWh/day, which are summarized in Supplementary Table 1. Furthermore, there is a high correlation (i.e., 83.8 %) between CO_2 emissions and EG over the whole period.

Fig. 1b shows no sharp decline in CO_2 emissions, except around 2020, which is strongly related to the pandemic [26]. In the remaining periods, a smooth and steadily increasing trend in CO_2 emissions can be observed. Among the sectors, the power sector also has the highest share of CO_2 emissions, followed by industry, residential, and transportation. Accordingly, the power and industrial sectors are highly volatile, as can be seen in the Supplementary Table 1. For this reason, the power sector



The units are $MtCO_2$/Day for CO_2 Emissions and TWh/Day for EG.

Fig. 1. Progress of CO_2 Emissions and EG in China
The units are $MtCO_2$/Day for CO_2 Emissions and TWh/Day for EG.
Source: Carbonmonitor [25].

should be of particular interest in any empirical study to obtain a comprehensive and robust analysis.

Fig. 1c also shows no sharp decline in the EG except around 2020, which is related to the falling demand for energy due to the pandemic (Davis et al., 2022b). Subsequently, a smooth trend in EC can be observed, except for the February months. Coal has the leading role among EG sources, followed by renewable sources (hydro, wind, solar, in that order) as well as natural gas, nuclear, and oil at the bottom. Furthermore, coal and hydropower are more volatile than other EG sources, as shown in Supplementary Table 1. Accordingly, a disaggregated level EG should have been considered in the empirical analysis to obtain a better analysis due to the high variations among EG sources.

Focusing on these leading polluting countries is important because any progress in reducing CO_2 emissions in countries like China can help make the world carbon neutral. In addition, the use of high-frequency (daily) and disaggregated data in the analyses is highly helpful in obtaining robust results by taking into account dynamic relationships and possible external effects between variables. By taking country-specific conditions into account, much more specific policies can be developed in this way.

Many previous studies have used data with latency (e.g., Ref. [21,27,28,29]). However, it is now possible in many countries to work with high-frequency (i.e., low-latency) data (e.g., Ref. [11,13,15,30]). Although there are several studies that consider the marginal effect (ME) (e.g., Ref. [31–33]), based on the best knowledge, they either generally used low-frequency data or did not examine the Chinese case or did not consider all sectors to examine the ME of EG on CO_2 emissions at the disaggregated level using high-frequency up-to-date data. Thus, from these points of view, there is a gap in the literature.

To contribute to the literature and close the gap, the study empirically analyzes the Chinese case. In doing so, the study utilizes the KRLS method on high-frequency daily data at a disaggregated level for both EG and CO_2 emissions by including a total of six different estimation models for each sector. Such an approach allows the researchers to investigate the ME of EG on sectoral CO_2 emissions at the disaggregated level in China by considering recent potentially effective aspects. Thus, the study finds that the ME of each EG source varies by sector and constructed model, highlighting the externalities among EG sources as well as the higher capability of the KRLS method in estimating sectoral CO_2 emissions. The statistical significance of EG sources on CO_2 emissions also varies by sector, showing that some EG sources are more critical for some sectors. The KRLS method thus provides novel results for the ME of EG on sectoral CO_2 emissions in China at a disaggregated level.

By following the comprehensive methodology mentioned above, the study brings several innovations. First, the study examines the Chinese case by performing a disaggregated level analysis for both EG and CO_2 emissions by considering all possible sectors as well as EG options based on the energy mix. Second, the study differs from many current studies by using high-frequency daily data between 2019 and 2022, which is the most up-to-date data available. Therefore, the study considers the most current issues (e.g., pre and post-pandemic times, higher geopolitical tensions, and the current energy crisis). Third, the study constructs a total of six various estimation models based on China's energy mix for each sector. Thus, different potential components of EG sources are analyzed for their effects on sectoral CO_2 emissions. Fourth, the study applies the KRLS method to examine the ME of each EG source on sectoral CO_2 emissions. This is also important because many recent studies in the literature have focused on the mean-based effect, whereas this study presents an analysis of the ME rather than the mean effect of each EG source on sectoral CO_2 emissions.

In the following sections, the methodology is explained in the second section, the results are evaluated in the third section and the discussion and conclusion are presented in the final section.

2. Methodology

2.1. Variables

This study investigates the effect of EG on CO_2 emissions in detail by performing a disaggregated level analysis. In this context, a total of four sectors (i.e., TRA, IND, POW, RES), which account for 99 % of total CO_2 emissions in China, are considered. In addition, a total of seven EG sources (i.e., NEG, CEG, GEG, OEG, HEG, WEG, SEG), which account for 96 % of the total EG in China, and a total of three groups (i.e., FEG, REG, NEG) of these sources are considered. Data for both EG and CO_2 emissions are collected from Carbonmonitor [25]. Table 1 presents the details of the variables.

The logarithmic time series between January 1, 2019, and December 31, 2022, are used to account for elasticities in revealing the effect of the EG on sectoral CO_2 emissions.

2.2. Estimation models

Taking into account the variables explained above, various models are constructed to analyze the ME of EG on CO_2 emissions. In this context, a total of six models are created, which are explained in Table 2.

In the estimation of sectoral CO_2 emissions, Model 1 considers the main types of EG sources (i.e., FEG, REG, NEG) to examine the ME depending on the source.

In Model 2, a total of three fossil EG sources (i.e., CEG, GEG, OEG) are considered.

In Model 3, a total of three renewable EG sources (i.e., HEG, WEG, SEG) are taken into account.

In Model 4, a mixed model is constructed based on higher shares of the energy mix depending on the type of energy source (i.e., NEG, CEG, HEG).

In Model 5, a mix is constructed based on intermediate shares in the energy mix according to each source type (i.e., NEG, GEG, WEG).

In Model 6, a mixed model is constructed based on lower shares in the energy mix according to each source type (i.e., NEG, OEG, SEG).

2.3. Empirical methodology

To investigate the ME of EG on sectoral CO_2 emissions, the applied methodology is presented in Fig. 2.

In the empirical investigation, descriptive statistics of the variables as well as correlations are examined. Later, stationarities are analyzed using ADF [34] and PP [35] and nonlinearities using the BDS test [36] of the variables, as they play a role in the selection of the appropriate econometric approach. Finally, the KRLS method [37] is applied to

Table 1
Variables.

Symbol	Definition	Unit	Data Source
TRA	CO_2 Emissions in the Transport Sector	$MtCO_2$/Day	Carbonmonitor [25]
IND	CO_2 Emissions in the Industry Sector		
POW	CO_2 Emissions in Power Sector		
RES	CO_2 Emissions in Residential Sector		
FEG	EG from Fossil (CEG, GEG, OEG)	GWh/Day	Carbonmonitor [25]
REG	EG from Renewable (HEG, WEG, SEG)		
NEG	EG from Nuclear		
CEG	EG from Coal		
GEG	EG from Natural Gas		
OEG	EG from Oil		
HEG	EG from Hydro		
WEG	EG from Wind		
SEG	EG from Solar		

Table 2
Details of the estimation models.

Model Number	Name	Included Variables
1	Main	FEG, REG, NEG
2	Fossil	CEG, GEG, OEG
3	Renewable	HEG, WEG, SEG
4	Mixed	NEG, CEG, HEG
5	Mixed	NEG, GEG, WEG
6	Mixed	NEG, OEG, SEG

investigate the ME of the EG on sectoral CO_2 emissions at a disaggregated level.

2.4. KRLS method

This study applies the KRLS method by Hainmueller & Hazlett [37] for the empirical analysis. The KRLS method is a machine learning-based estimation model that provides valuable insights into the ME of explanatory variables (i.e., EG) on the dependent variable (i.e., sectoral CO_2 emissions) [38]. According to the inventors [37], the KRLS method *"is a superior method for solving regression and classification problems without relying on linearity or additivity assumptions by benefiting from machine learning. It also constructs a flexible hypothesis space using kernels as radial basis functions and finds the best-fitting surface in this space by minimizing a complexity-penalized least squares problem. Therefore, it is well suited for social science studies as it avoids strong parametric assumptions and still allows for an interpretation analogous to generalized linear models, while also allowing for more complex interpretations to study nonlinearities, interactions, and heterogeneous effects"*. The Gaussian kernel function used in the KRLS method is shown in Eq. (1). The Gaussian kernel function used in the KRLS method is shown in Eq. (1).

$$k(x_j, x_i) = e^{-\frac{|x_j - x_i|^2}{\sigma^2}} \tag{1}$$

where σ^2 is the bandwidth of this function and x_j and x_i are the covariates. If the difference between the covariances is too large, the kernel reaches the value 0; if they are close to each other, the kernel reaches its maximum value. The value of the function can be evaluated as in Eq. (2) for a specific point (x^*).

$$y = f(x) = \sum_{i=1}^{N} c_i k(x^*, x_i) \tag{2}$$

where c_i denotes the weight for independent variables and f(x) represents a linear integration of the kernels. Eq. (2) can be stated in vector form as follows:

$$y = Kc = \begin{bmatrix} k(x_1, x_1) & k(x_1, x_2) & \cdots & k(x_1, x_N) \\ k(x_2, x_1) & \ddots & & \\ \vdots & & & \\ k(x_N, x_1) & & & k(x_N, x_N) \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \\ c_N \end{bmatrix} \tag{3}$$

where c shows the scaled weights. Considering equations (2) and (3), the final partial derivatives are estimated based on kernel regularized least squares and pointwise MEs using Eq. (4):

$$\frac{\widehat{\delta_y}}{\delta x_j^{(d)}} = \frac{-2}{\sigma^2} \sum_i c_i e^{\frac{-\|x_i - x_j\|^2}{\sigma^2}} \left(x_i^{(d)} - x_j^{(d)}\right) \tag{4}$$

where $\frac{\widehat{\delta_y}}{\delta x_j^{(d)}}$ shows the partial derivatives, e denotes the exponential term, and σ^2 illustrates the kernel bandwidth.

In the empirical analysis, the study estimates the following models for each sector by applying the KRLS method:

$$\text{Sectoral } CO_2 = f\,(FEG, REG, NEG) \tag{5}$$

$$\text{Sectoral } CO_2 = f\,(CEG, GEG, OEG) \tag{6}$$

$$\text{Sectoral } CO_2 = f\,(HEG, WEG, SEG) \tag{7}$$

$$\text{Sectoral } CO_2 = f\,(NEG, CEG, HEG) \tag{8}$$

$$\text{Sectoral } CO_2 = f\,(NEG, GEG, WEG) \tag{9}$$

$$\text{Sectoral } CO_2 = f\,(NEG, OEG, SEG) \tag{10}$$

where sectoral CO_2 denotes each sector in China, which consists of four main sectors (i.e., TRA, IND, POW, RES), while all variables, including explanatory ones, are detailed in Table 1.

3. Results

3.1. Preliminary statistics

Before proceeding with the empirical analysis, the study first examines the data characteristics of the variables listed in the Supplementary Table 1. According to this, the power sector plays the leading role in sectoral CO_2 emissions, followed by industry, residential, and

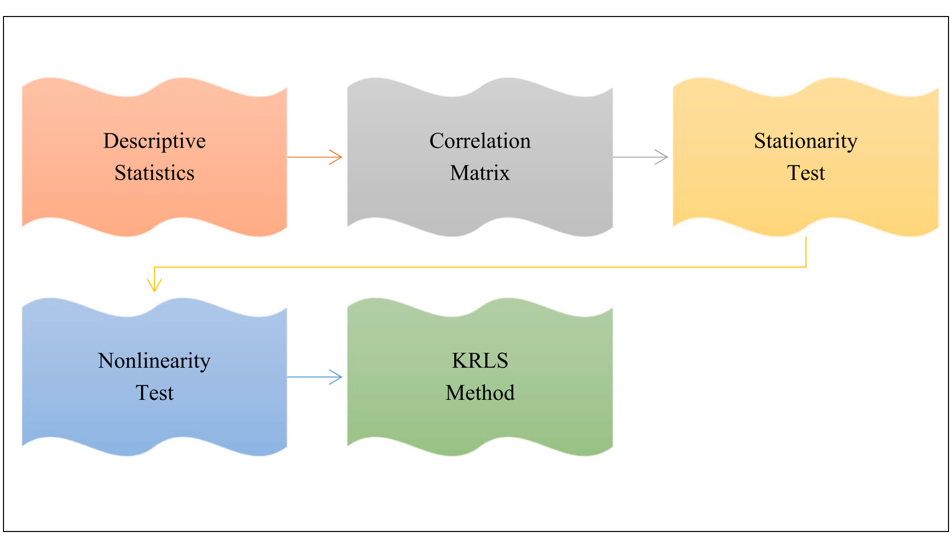


Fig. 2. Empirical methodology steps.

transport sectors. These sectors also show the highest volatility in this order. Coal EG has the leading role among EG sources, followed by hydro, wind, and solar energy. Moreover, these EG sources show the highest volatility in this regard. Furthermore, all these sectoral CO_2 emissions and EG sources show a nonnormal distribution.

As reported in Supplementary Table 2, each EG source shows a relatively low positive correlation with CO_2 emissions in the transport, industry, and power sectors, except for coal in the power sector. Furthermore, with the exception of coal and wind, all EG sources show a relatively low negative correlation with CO_2 emissions from the residential sector. Thus, while the overall correlation between EG and CO_2 emissions demonstrates a critical relationship, a low correlation between EG sources and sectoral CO_2 emissions allows researchers to obtain robust results.

According to Supplementary Tables 3 and 4, all variables are stationary at first difference based on both the ADF and PP tests. There is also a nonlinear structure for all variables.

By considering all preliminary statistics altogether, which have volatility as well as are nonnormal and nonlinear, the study applies the KRLS method as a machine learning-based approach for further empirical investigations.

3.2. *Transport sector CO_2 emissions*

First, the CO_2 emissions of the transport sector are examined using six various models, which are constructed using the KRLS method. The graphical details of the models can be found in Supplementary Fig. 1, and the results based on the coefficients are shown in Table 3.

In Model 1, which is the highest model of all with an estimation capacity of 80.5 %, FEG has a positive but decreasing ME at a higher TRA level, while NEG has a negative but increasing ME at a higher TRA level.

In Model 2, CEG has a positive but decreasing ME at higher TRA levels, while GEG has a negative but increasing ME at higher TRA levels. In Model 3, HEG has a positive but decreasing ME on a higher level of TRA, while SEG has a negative but increasing ME on a higher level of TRA.

In Model 4, NEG has a negative but increasing ME at a higher level of TRA, while CEG has a positive but decreasing ME at a higher level of TRA. On the other hand, HEG has a negative but increasing ME at lower and middle levels of TRA, while it turns out to have a positive but decreasing ME at higher levels of TRA.

In Model 5, NEG has a positive but decreasing ME at a higher level of TRA, while WEG has a negative but increasing ME at a higher level of TRA. In Model 6, NEG has a positive but decreasing ME at a higher level of TRA. However, SEG has a positive but decreasing ME at lower and middle levels of TRA, while it turns out to have a negative but increasing ME at higher levels of TRA.

Overall, Model 1 has the highest estimation capacity (80.5 %), followed by Models 4, 6, 2, 5, and 3, respectively. In summary, the evaluation of all these models suggests that the optimal solution is to limit FEG and CEG and promote SEG to ensure carbon neutrality in the transport sector.

3.3. *Industry sector CO_2 emissions*

After the transport sector, CO_2 emissions in the industry sector are examined by considering six various models constructed through the KRLS method. The graphical details of the models can be found in Supplementary Fig. 2, and the results based on the coefficients are shown in Table 4.

In Model 1, FEG has a positive but decreasing ME at the lower and middle levels, while it has a negative and increasing effect at the higher levels of IND. In contrast, REG has a positive ME at all levels of IND. NEG has a negative but increasing ME at lower levels, while it has a positive but decreasing ME at middle levels and a positive and horizontal ME at higher levels of IND.

In Model 2, CEG has a positive but decreasing ME at lower levels of IND, while it has a negative but increasing ME at middle and higher levels. Although its effect varies, GEG has a positive ME at all levels of the IND. Similarly, OEG has a positive but decreasing ME at all levels of the IND.

In Model 3, HEG, WEG, and SEG have a positive ME across all levels of IND. However, the effect varies depending on the level. In particular, WEG has a negative and increasing ME at higher levels and SEG has a negative and decreasing effect at lower levels of IND.

In Model 4, which has the highest estimation capacity among all models at 84 %, NEG has a positive ME at the lower and middle levels of IND, it has a negative and increasing effect at the higher level of IND. On the other hand, WEG has a positive and horizontal effect at lower and middle levels, while the effect becomes positive and increases at higher levels of IND.

In Model 5, NEG has a positive ME at the lower and middle levels of IND, while it has a negative and increasing effect at the higher level of IND. On the other hand, GEG has a negative but increasing ME at the

Table 3
KRLS results for transport sector CO_2 emissions.

Variable	Statistics	Models Based on EG Sources					
		1	2	3	4	5	6
		Main	Fossil	Renewable	Mixed	Mixed	Mixed
FEG	Coef.	0.45					
	p-value	0.00					
REG	Coef.	0.01					
	p-value	0.53					
NEG	Coef.	−0.16			−0.23	0.26	0.20
	p-value	0.00			0.00	0.00	0.00
CEG	Coef.		0.42		0.58		
	p-value		0.00		0.00		
GEG	Coef.		−0.06			−0.01	
	p-value		0.02			0.70	
OEG	Coef.		0.03				−0.01
	p-value		0.20				0.58
HEG	Coef.			0.20	0.08		
	p-value			0.00	0.00		
WEG	Coef.			0.02		−0.08	
	p-value			0.46		0.00	
SEG	Coef.			−0.10			−0.07
	p-value			0.00			0.00
R^2 (Explanatory Power)		80.5	66.0	63.9	75.9	64.9	71.9

Table 4
KRLS results for industry sector CO_2 emissions.

Variable	Statistics	Models Based on EG Sources					
		1	2	3	1	5	6
		Main	Variable	Statistics	Main	Variable	Statistics
FEG	Coef.	0.11					
	p-value	0.00					
REG	Coef.	0.22					
	p-value	0.00					
NEG	Coef.	0.14			0.21	0.47	0.18
	p-value	0.00			0.00	0.00	0.00
CEG	Coef.		−0.22		0.03		
	p-value		0.00		0.07		
GEG	Coef.		0.26			−0.12	
	p-value		0.00			0.00	
OEG	Coef.		0.39				0.04
	p-value		0.00				0.02
HEG	Coef.			0.23	0.14		
	p-value			0.00	0.00		
WEG	Coef.			0.20		0.03	
	p-value			0.00		0.00	
SEG	Coef.			0.05			0.10
	p-value			0.02			0.00
R^2 (Explanatory Power)		83.9	67.8	82.6	84.0	81.3	83.1

lower and middle levels of IND, while it becomes a positive and increasing ME at the higher level of GEG. In contrast, WEG has a positive ME, while its trend (i.e., increasing or decreasing) varies depending on the level of IND. In Model 6, NEG and SEG have a predominantly positive ME, which varies depending on the level of the IND. However, OEG has a positive but decreasing ME at lower and middle IND levels, while it becomes a negative and decreasing ME at higher IND levels.

Overall, Model 4 has the highest estimation capacity (84 %) followed by Models 1, 6, 3, 5, and 2, respectively. After evaluating all models, it can be concluded that the optimal solution is to reduce FEG and OEG and increase GEG to ensure carbon neutrality in the industry sector.

3.4. Power sector CO_2 emissions

Later, CO_2 emissions in the power sector are analyzed through six various models constructed by applying the KRLS method. The graphical details of the models can be found in Supplementary Fig. 3 and the results based on the coefficients are shown in Table 5.

In Model 1, FEG has a positive ME, while its strength varies across the different levels of the POW. REG also has a positive ME, while it decreases at a lower level, is almost insignificant at the middle level, and increases at higher levels of the POW. In Model 2, which is the best model of all with an estimation capacity of 99.8 %, CEG has a positive ME, while its explanatory power varies at different levels of the POW. GEG has a positive, but almost insignificant ME at all levels. OEG also has a positive, but decreasing ME at lower POW levels, a non-significant effect at middle POW levels, and an increasing effect at higher POW levels.

In Model 3, WEG, the only statistically significant variable, has a positive but decreasing ME at lower POW values, while it becomes almost insignificant in the middle and increases at higher POW values. In Model 4, NEG has a negative but increasing ME at the lower level of POW, while it becomes almost significant at the middle level, and is negative but horizontal at the higher level of POW. On the other hand, CEG has a positive ME at all levels, but its power is weaker at lower and higher levels of the POW, while it is much stronger at the middle level of the POW.

In Model 5, NEG and GEG have a positive but horizontal ME across

Table 5
KRLS results for power sector CO_2 emissions.

Variable	Statistics	Models Based on EG Sources					
		1	2	3	1	5	6
		Main	Variable	Statistics	Main	Variable	Statistics
FEG	Coef.	0.92					
	p-value	0.00					
REG	Coef.	−0.00					
	p-value	0.09					
NEG	Coef.	0.00			0.02	0.47	0.81
	p-value	0.38			0.00	0.00	0.00
CEG	Coef.		0.87		0.92		
	p-value		0.00		0.00		
GEG	Coef.		0.04			0.39	
	p-value		0.00			0.00	
OEG	Coef.		0.03				0.08
	p-value		0.00				0.01
HEG	Coef.			−0.02	0.00		
	p-value			0.27	0.77		
WEG	Coef.			0.20			
	p-value			0.00		0.01	
SEG	Coef.			0.01			−0.08
	p-value			0.64			0.00
R^2 (Explanatory Power)		99.7	99.8	75.5	99.7	85.8	79.2

all levels of the POW. On the other hand, WEG has an almost insignificant ME across all levels. In Model 6, NEG has a positive but increasing ME on the higher level of POW. However, OEG has a positive but almost insignificant ME at the lower and middle levels of the POW, while it proves to have a negative and increasing ME at the higher levels of the POW. In contrast, SEG has a negative and relatively horizontal ME at the middle and higher levels of the POW.

Overall, Model 2 has the highest estimation capacity (99.8 %) followed by Models 4, 1, 5, 6, and 3, respectively. According to the models, it can be summarized that the optimal solution is to dismantle FEG, CEG, GEG, and OEG, and support REG and WEG to achieve carbon neutrality in the power sector.

3.5. *Residential sector CO_2 emissions*

Finally, CO_2 emissions in the residential sector are analyzed through six various models constructed using the KRLS method. The graphical details of the models can be found in Supplementary Fig. 4, and the results based on the coefficients are presented in Table 6.

In Model 1, FEG has a positive but varying ME across the different levels of RES. REG has a negative ME, but this decreases as the RES level increases. NEG also has a positive ME, which is stronger at lower and higher levels of RES. In Model 2, CEG has a clear positive ME, while GEG has a negative ME at all levels of RES. On the other hand, OEG has a negative ME, which is stronger at middle levels and almost insignificant at higher levels of RES.

In Model 3, HEG and SEG have a negative ME, while WEG has a positive ME across all levels of RES. In Model 4, which has the highest estimation capacity among all models at 85.9 %, CEG has a positive, but HEG has a negative ME at all levels of RES, while their effects vary.

In Model 5, NEG has a negative ME, while GEG and WEG have a positive ME across all levels of RES. In Model 6, NEG and OEG have a positive ME, while SEG has a negative ME across the levels of RES.

Overall, Model 4 has the highest estimated capacity (85.9 %) followed by Models 3, 1, 6, 2, and 5 respectively. Summarizing the evaluation of all these models, it can be concluded that the optimal solution is to reduce FEG, CEG, and OEG, and promote REG, SEG, and HEG to make the residential sector carbon neutral.

4. Discussion and conclusion

This research analyzes the dynamic effects of disaggregated level EG sources on sectoral CO_2 emissions in China. Using the KRLS method, the study presents an analysis of the MEs of EG sources on sectoral CO_2 emissions to make the sectors carbon-neutral.

The results show that the EG does not have a linear effect on sectoral CO_2 emissions, indicating that it follows a nonlinear pathway. The study also determines that the ME of EG on sectoral CO_2 emissions has a varying structure, which can be either incremental or diminishing, based on the sectors, the EG sources, and the constructed estimation models. Some EG sources have a higher importance for CO_2 emissions of some sectors because the statistical significance of each EG source for CO_2 emissions is different. Moreover, the KRLS method has a higher estimation capability, reaching ~99.8 %.

In summary, it can be said that for both EG sources and sectoral CO_2 emissions, several points have come to the fore in ensuring carbon neutrality.

- In the transport sector, EG from fossil fuels and coal has a higher increasing ME, which should be curbed, while EG from solar has a stronger decreasing ME.
- In the industry sector, EG from fossil fuels and oil has a higher increasing ME, which should be curbed, while EG from gas has a stronger decreasing ME.
- In the power sector, the leading sector in terms of higher estimation capacity by the KRLS method, EG from fossil fuels and coal has a higher increasing ME, which should be curbed, while EG from renewables and wind has a stronger decreasing ME.
- In the residential sector, EG from fossil fuels, coal, and oil has a higher increasing ME, which should be curbed, while EG from renewables, solar, and hydro has a stronger decreasing ME.
- Overall, the ME of EG on sectoral CO_2 emissions has a varying structure, and some EG sources have no significant effect in some estimation models.

The outcomes mainly prove the changing MEs of the EG on sectoral CO_2 emissions in China. Although some studies consider the ME, they have not made a comprehensive analysis because they either use high-frequency data (e.g., yearly data by Ref. [31,33]) or examined China but did not consider all sectoral CO_2 emissions (e.g. Ref. [32], for the only household sector). Hence, by differentiating from such studies, this study provides further evidence about the ME of EG on CO_2 emissions at disaggregated levels by using recent high-frequency data for the Chinese case.

Table 6
KRLS results for residential sector CO_2 emissions.

Variable	Statistics	Models Based on EG Sources					
		1	2	3	1	5	6
		Main	Variable	Statistics	Main	Variable	Statistics
FEG	Coef.	0.53					
	p-value	0.00					
REG	Coef.	−1.15					
	p-value	0.00					
NEG	Coef.	0.35			−0.10	−0.45	0.18
	p-value	0.00			0.05	0.00	0.03
CEG	Coef.		2.02		0.54		
	p-value		0.00		0.00		
GEG	Coef.		−1.31			0.52	
	p-value		0.00			0.00	
OEG	Coef.		−0.14				0.57
	p-value		0.01				0.00
HEG	Coef.			−0.30	−0.42		
	p-value			0.00	0.00		
WEG	Coef.			0.81		0.45	
	p-value			0.00		0.00	
SEG	Coef.			−0.87			−0.72
	p-value			0.00			0.00
R^2 (Explanatory Power)		80.4	69.4	85.9	85.9	58.6	70.1

Considering the main points summarized above, it is critical to state that Chinese policymakers should not focus on both total EG and CO_2 emissions, rather, they should care about each EG source and the CO_2 emissions of each sector resulting from EG. For this reason, EG is expected to increase in the Asian region including China [39]. Thus, it is important to create the ideal combination for EG to make the sectors carbon neutral.

China is using energy conservation policies and taxes on petroleum products to reduce CO_2 emissions [40]. With the 14th Five-Year Plan for Renewable Energy, China aims to increase the share of renewable EG to 33 % by 2025 and thus reduce CO_2 emissions [41]. In addition, China is implementing increased policy measures, such as increasing the supply of renewable energy, improving fuel efficiency in transportation, improving building efficiency, and continuing afforestation measures to reduce CO_2 [42]. In addition, Qi et al. [43] state that the Chinese government can achieve a 3.4 % annual reduction in carbon intensity if it increases the share of renewables in energy consumption to 36 % by 2030, limits the annual growth of energy consumption to about 1.3 % and brings total energy consumption to 5.5 billion tons of coal equivalent. In this context, it is clear that China's incentives for renewable EG are important to reduce CO_2 emissions and carbon intensity. In light of the current study's findings, China's policymakers need to select appropriate renewable EG sources to reduce CO_2 emissions on a sectoral basis and introduce tax exemptions that increase efficiency in the use of renewable EG.

Chinese policymakers should also consider the externalities among EG sources in the context of energy-related environmental policy. As the results demonstrate, some EG components are not effective in the reduction of sectoral CO_2 emissions, while others have a much stronger effect. Therefore, following a linear approach is not the right way to go.

The use of a certain amount of fossil EG sources (e.g., gas in Model 2 for the transport sector; and oil in Model 3 for the residential sector) is not necessarily harmful for sectoral CO_2 emissions. Even if the use of such sources causes a certain amount of CO_2 emissions, their marginal contribution is relatively small.

The ME analysis leaves temporary room for growth, but accounting for the current use of energy sources is critical to China's carbon neutrality. According to EI [5], China generated electricity from 63.8 % fossil sources, 27.8 % renewable sources, 4.8 % nuclear sources, and 3.6 % other sources in 2019–2022. It is therefore still important to enable the transition to clean energy sources in EG. China still has a long way to go from this point.

The structure of the current sectors is another important point. According to Carbonmonitor [25], the power and industry sectors in China play a leading role in emitting higher CO_2 emissions, with shares of 44.8 % and 39 %, respectively for the period 2019–2022. The transformation of these sectors into eco-friendly structures is therefore inevitable if China is to achieve its carbon neutrality goals. In this context, in addition to the energy transition on the supply side, the application of various measures, such as the electrification of these sectors on the demand side can also be helpful in re-shaping the Chinese sectors [44].

Finally, while this study focuses on the marginal impacts of the EG on sectoral CO_2 emissions, it also has some limitations in nature. First, the study focuses on analyzing current data using the KRLS method for estimation rather than using it for future forecasting through a simulation approach. Second, the study considers disaggregated level data for EG on a source basis and CO_2 emissions on a sector basis. However, it does not take into account geographical differences, which could be important in the case of China. In the future, new studies can take these points into account when formulating new content and the literature can become much richer in this way.

Disclosure statement

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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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.

Data availability

Data will be made available on request.

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Not applicable.

Appendix A. Supplementary Information

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Acronyms

ADF	Augmented Dickey-Fuller
BDS	Broock, Scheinkman, Dechert, and LeBaron
CO_2	Carbon Dioxide
EG	Electricity Generation
EI	Energy Institute
GWh	Gigawatt hours
KRLS	Kernel-Based Least Squares
ME	Marginal Effect
PP	Phillips-Perron
TWh	Terawatt hour
US	United States
WB	World Bank

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