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CO$_2$ Emissions in China: Does the Energy Rebound Matter?

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Abstract: Enhancing energy efficiency is globally regarded as an effective way to reduce carbon emissions. In recent years, the energy efficiency of China has gradually improved; however, energy consumption and CO$_2$ emissions are still increasing. To better understand the reasons for this, we evaluated the energy rebound effect (RE) of 30 provinces in China over the period 2001–2017 by employing stochastic frontier analysis (SFA) and the system generalized method of moments (system-GMM) approach, and explored the extent to which the RE affects CO$_2$ emissions. Asymmetric and regional heterogeneity analyses were also conducted. The results indicate that the national average RE was 90.47% in the short run, and 78.17% in the long run, during the sample period. Most of the provinces experienced a partial RE, with a backfire effect occurring in some provinces such as Guangxi and Henan. The RE was associated with significant increases in CO$_2$ emissions; specifically, a 1% increase in the short-run RE led to an increase in CO$_2$ emissions of approximately 0.818%, and a 1% increase in the long-run RE resulted in an increase in CO$_2$ emissions of approximately 0.695%. Moreover, significant regional differences existed in the impact of the RE on CO$_2$ emissions; in regions with high emissions and a high RE, the CO$_2$ reduction effect from the marginal decline in the RE was much more pronounced than that in other regions.

Keywords: energy rebound effect; CO$_2$ emissions; system generalized method of moments; regional heterogeneity

1. Introduction

In recent years, global warming has become a crucial issue worldwide [1,2]. As the main contributor to increasing temperatures, CO$_2$ emissions, and their reduction, have become the primary focus. Governments hope to achieve the goals of energy conservation and emission reduction by implementing energy efficiency improvement policies. However, the existence of the rebound effect poses a potential challenge to the emission reduction targets. The rebound effect (RE) refers to the fact that the expected energy savings resulting from the improved energy efficiency may be offset to a certain degree due to the additional energy demand caused by the change in economic agents' behavior [3–5]. A study by Fowlie et al. [6] highlighted that the actual energy savings resulting from the enhancement of energy efficiency are lower than the expected energy savings due to the existence of the RE, resulting in misalignment between energy policies and energy-saving goals. In view of the additional energy demand generated from the RE, special attention deserves to be paid to the environmental impacts (i.e., CO$_2$ emissions) of the RE.

During the past two decades, the Chinese government has implemented a series of policies to improve energy efficiency to reduce energy consumption and CO$_2$ emissions. As Figure 1 shows, China's energy efficiency has gradually improved under these policies in recent years. However, contrary to our expectations, although China's energy efficiency improved over this period, its overall energy consumption did not decline, but increased (see Figure 2). Specifically, China's total energy consumption nearly tripled from 2001 to

2021, from 1555 million tons of coal equivalent (Mtce) in 2001 to 5240 Mtce in 2021 [7]. At the same time, CO_2 emissions in China also increased over this period. From 2001 to 2019, total carbon emissions in China increased by nearly 3.7 times, from 3284 metric tons (Mt) in 2001 to 12,290 Mt in 2019 [8]. Figure 3 depicts the evolution trend in CO_2 emissions in 30 provinces in China; it can be seen from Figure 3 that CO_2 emissions gradually increased during the past decades.

The main driver behind this trend is the RE, which offsets potential energy savings from improved energy efficiency by generating new energy demand and thereby carbon emissions. However, the potential impact of the RE on CO_2 emissions is often overlooked by energy policies. Since China is the world's major CO_2 emitter, it is worth paying attention to the impact of the RE on CO_2 emissions, which would also provide valuable references for other countries with a high RE and high emissions.
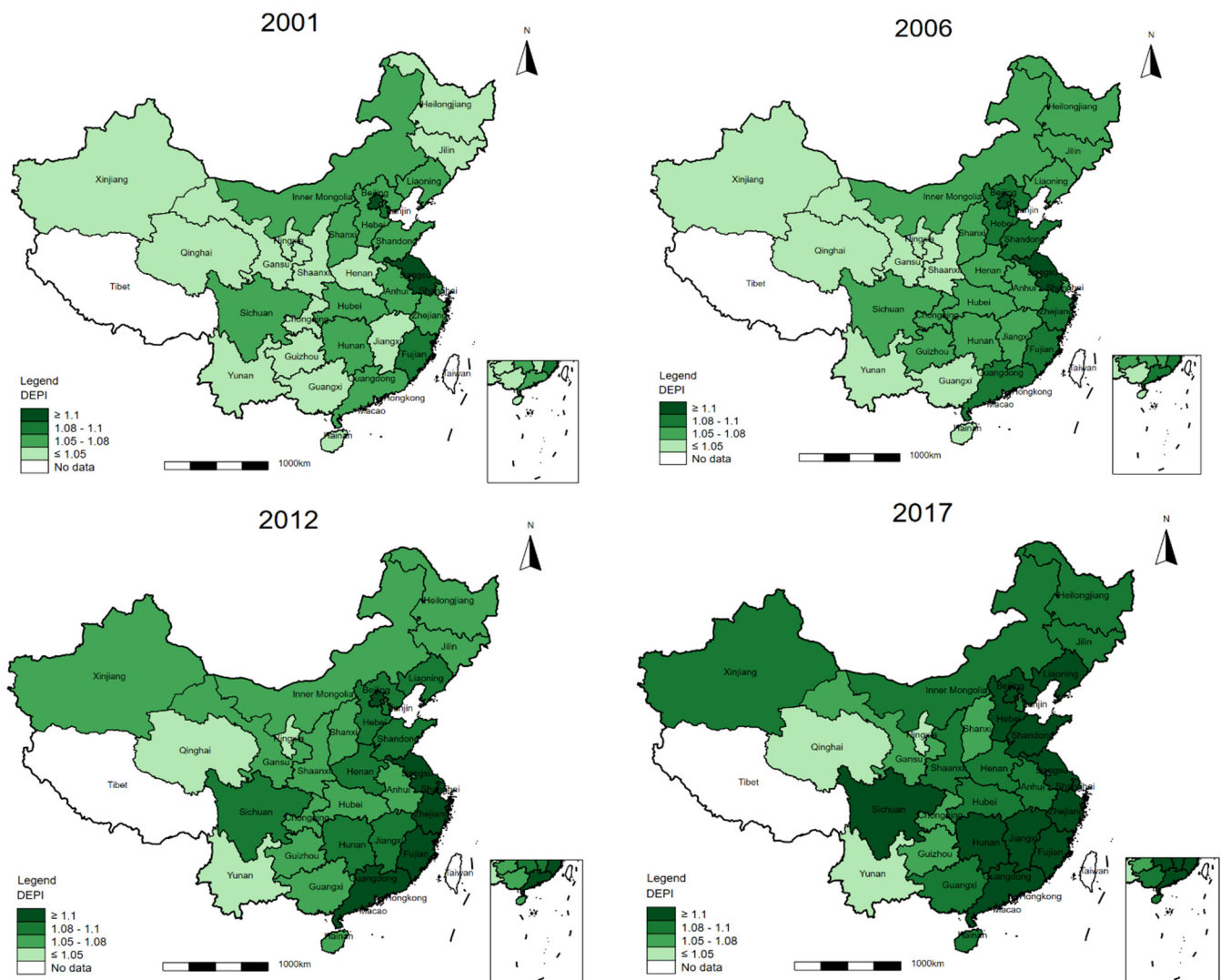
Figure 1. Spatial distribution of energy efficiency performance in 30 provinces of China.
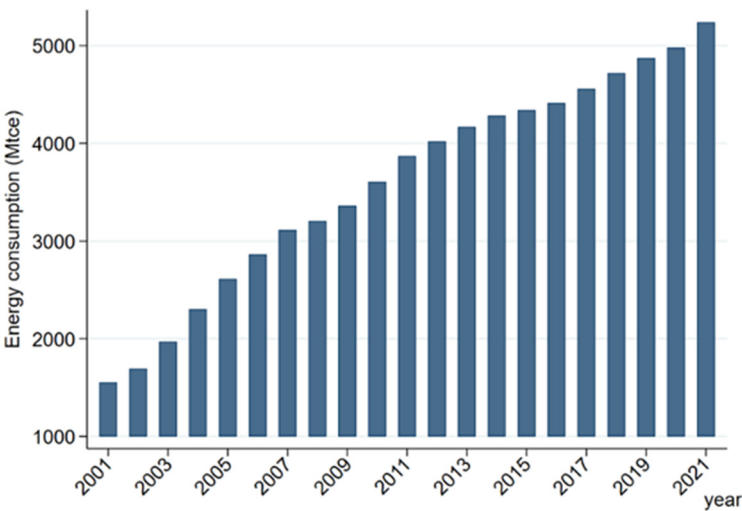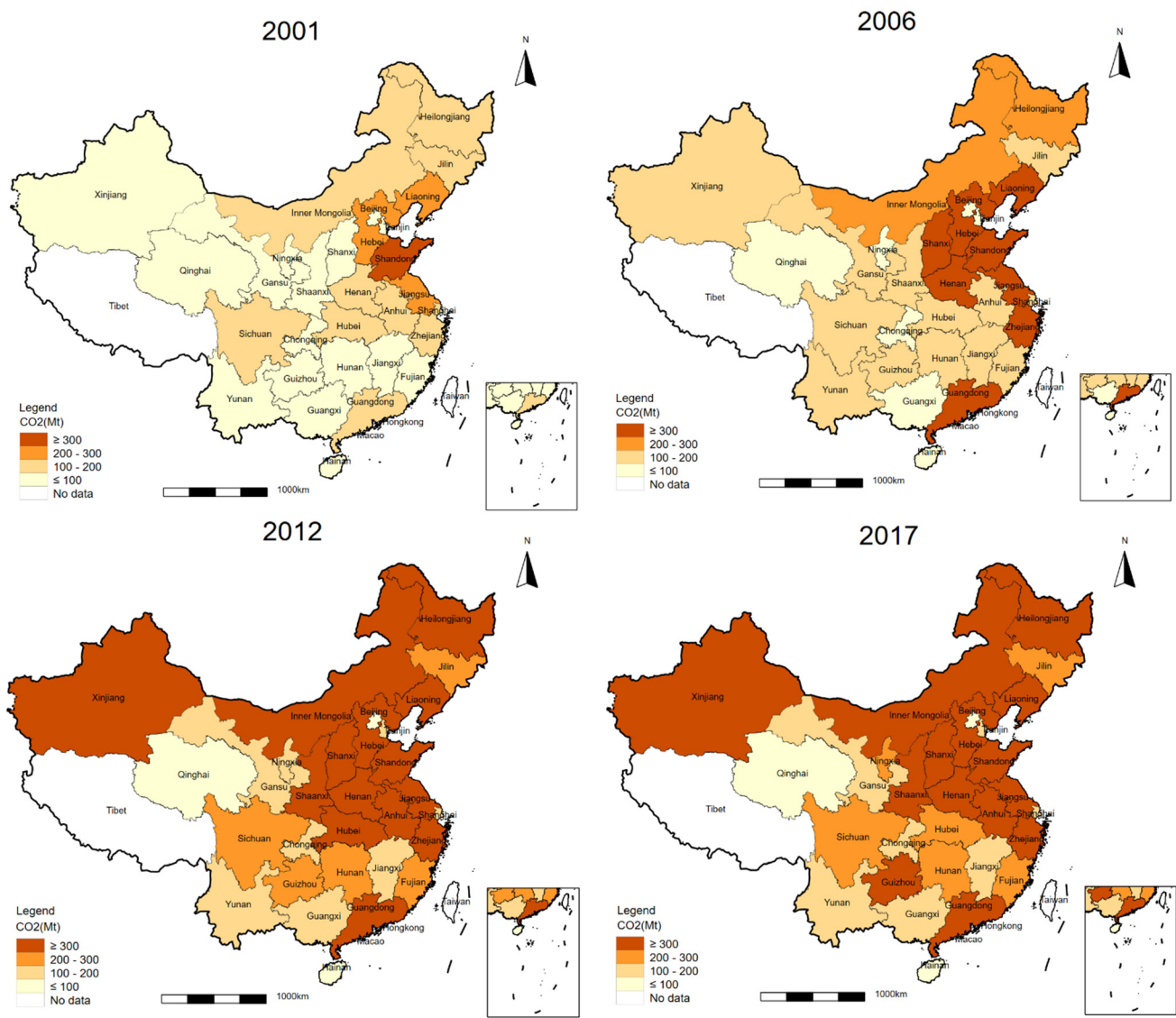
Figure 2. Energy consumption in China, 2001–2021.

Figure 3. CO$_2$ emissions in China across 30 provinces.

In recent years, estimating the magnitude of the RE has become the focus of this research. Many scholars have evaluated the RE based on various approaches [9–12]; however, there is still a debate about its magnitude due to the lack of unified evaluation mechanisms both in theory and practice [13,14]. Furthermore, to date, much research has been undertaken to detect the potential drivers of CO_2 emissions in terms of various aspects [15,16]; however, the potential impacts of RE on CO_2 emissions have rarely been systematically investigated, especially for the case of China. To this end, several questions aroused our interest: (1) What is the extent of China's current energy RE? Does the RE behave differently in the short and long term? (2) To what extent does the RE impact CO_2 emissions in the short and long term? What is the direction of this impact? (3) Does the RE have asymmetric and heterogeneous regional impacts on CO_2 emissions? It is essential to examine the above issues for a deeper understanding of the RE and its role in CO_2 emissions, and thus provide new insights for policymakers to formulate emission reduction policies.

Accordingly, we first assessed the RE of 30 provinces in China from 2001 to 2017 by employing stochastic frontier analysis (SFA) and the system generalized method of moments (system-GMM) approach, and explored the extent to which the RE affects CO_2 emissions. Asymmetric and regional heterogeneity analyses were also conducted. The contributions of this study are as follows: (1) By constructing a dynamic comprehensive energy efficiency index, we calculated the economy-wide RE of 30 provinces in China for the short and long terms. To the best of our knowledge, RE estimates are still lacking a consensus, and economy-wide RE studies at the sub-national level in China are rare. Considering the vast territory, resource endowment, and economic development differences in China, it is still necessary to investigate the RE at the sub-national level for a deeper understanding of the RE and to provide policymakers with new insights to formulate specific measures to control the RE. (2) To date, many studies have examined the potential drivers of CO_2 emissions; however, very few studies have systematically explored the potential impacts of the RE on CO_2 emissions, especially for the case of China. To make a marginal contribution to the existing literature based on this insight, we systematically explored the dynamic impacts of the RE in the short and long term on CO_2 emissions based on the balanced panel dataset of 30 provinces in China, which offers strong evidence for capturing the potential drivers behind the continuous increase in CO_2 emissions. This also provides valuable references for other countries with a high RE and high emissions, by offering policymakers new insights for designing short- and long-run policies from the perspective of the RE to reduce the carbon emissions. (3) Taking into account the regional heterogeneity, we also investigated the potential asymmetry and heterogeneity in the impact of the RE on CO_2 emissions by dividing the full sample into four regions based on the distribution of the RE and CO_2 emissions. This provides detailed evidence to design more specific regional policies to control the RE and CO_2 emissions.

The remainder of the paper is organized as follows. Section 2 presents a brief literature review of the RE and determinants of CO_2 emissions. Section 3 evaluates the RE of 30 provinces in China based on the stochastic frontier analysis (SFA) and system generalized method of moments (system-GMM) approach. In Section 4, we present an econometric model to explore the potential impacts of the RE on CO_2 emissions; the data sources of all relevant variables are also reported in this section. Then, we discuss the impacts of the RE in the short and long run on CO_2 emissions according to the econometric model estimation results in Section 5. In Section 6, we further conduct asymmetric and regional heterogeneity analysis of the impact of the RE on CO_2 emissions. The final section presents the conclusions of this study.

2. Literature Review

2.1. Existing Research on the Energy Rebound Effect

In recent years, as a result of the increasing prominence of climate change, the energy rebound has attracted many scholars' attention. The concept of the rebound effect dates

back to Jevons [17]. In his book "Coal problem", Jevons [17] noted that the increment in natural resource efficiency would result in increased consumption of such resources, rather than a decrease, which is known as the "Green paradox". Subsequently, Daniel Khazzoom [18] and Brookes [19] initiated the modern rebound effect theory and debated the existence of a backfire effect in the real economy. Since then, many scholars have significantly explored the rebound effect.

In the literature, the measurement methods of the rebound effect are classified into two strands: computable general equilibrium (CGE) models and non-CGE models. In contrast to non-CGE models, CGE models are based on social accounting matrices for the relevant economies, and they consist of a set of simultaneous equations describing the behavior of producers, consumers, and other economic actors, together with the interdependencies and feedback between the different sectors [20]. Specifically, Bye et al. [9] calculated the energy rebound of Norway by employing a CGE model, and results indicate that Norway's RE reaches 40% for the sample period. On the basis of a CGE model, Anson and Turner [21] investigated the RE of UK's commercial transport sector. His study found that a 5% increase in energy efficiency in the commercial transportation sector resulted in a 39% rebound in the use of petroleum commodities in this industry and the whole economy. Based on the same method, Hanley et al. [22] explored the RE of Scotland's economy and identified a backfire effect in Scotland's power and non-power sectors, with rebounds of 131% and 134%, respectively. However, the CGE approach has been criticized by some scholars due to its strict assumptions, such as constant substitution elasticity between different input factors and complete market clearing [20], and it poses high requirements for data quality [23]. Therefore, some scholars also explored non-CGE models to estimate the RE, such as macroeconomic models, econometric analysis, and the growth accounting approach. Specifically, based on the macroeconomic model, i.e., the Solow growth model, Saunders [10] estimated Sweden's energy RE for a long period between 1850 and 2000, and found that the average rebound value was approximately 60%. On the same basis, Barker et al. [24] explored the global RE for the period of 2010–2030 and indicated that the average value of the energy RE was 52%. With regard to econometric analysis, Adetutu et al. [11] explored the RE of 55 countries by employing stochastic frontier analysis and found that the RE reaches 90% in the short term, and −36% in the long term. Wei et al. [12] estimated the RE of 40 regions for the period 1995–2009 by decomposing the change in output caused by energy intensity variation, and found that the average RE is 150%. Some scholars also tried to evaluate the RE based on the growth accounting approach. For instance, Lin and Liu [25] estimated China's RE between 1981 and 2009 by employing the growth accounting approach, and indicated that the average value of the RE was 53.2%. By utilizing the same technique, Shao et al. [14] evaluated China's RE for the period 1954–2010 and found that the average value was 47% before 2000, and 37% after 2000. In summary, compared to the complex CGE model, studies based on non-CGE models have also contributed valuable insights; however, they also present a number of significant limitations. For instance, Saunders [10] and Wei et al. [12] adopted aggregate production functions, which were not believed to be appropriate by some scholars [26,27]. The growth accounting studies underestimated rebound effects, owing to their assumption that increases in output are the primary driver of rebound, which neglects other mechanisms of RE [5,28]. Overall, a large amount of work has been conducted to examine the rebound effect by developing different approaches; however, estimation results are still not consistent due to the lack of unified evaluation mechanisms, both in theory and practice [20,29].

As China has become the world's major energy consumer, China's energy rebound has also attracted many scholars' attention. The related literature has mainly concentrated on exploring the RE (direct or indirect) of different industries, regions, or sectors (e.g., households). Specifically, Lin and Zhu [4] evaluated the direct RE of Chinese residents' electricity consumption for the period 2010–2018, and the results indicate that the average RE was 48%. Based on the time series data of 1991–2016, Shao et al. [30] explored the RE of

Shanghai, China, and found the total RE during this period reached 93.96%. Liu et al. [31] evaluated the RE of the coal industry in China from 2009 to 2019, and the results indicate that the average RE of the industry was 30.27%. Meng and Li [32] estimated the direct RE of the electricity sector in 30 Chinese provinces for the period 2009–2018, and found that the average RE was 75.21%. On the basis of a panel dataset over the period 2003–2013, Zhang and Lin [33] calculated the RE of the transport sector in China, and showed the extent of the RE varied from 7.2% to 82.2%. In addition, Du et al. [34] estimated the RE level of the Chinese urban residential sector for the period 2001–2014, and the results indicate that the average RE was 65.4%. Li and Lin [35] conducted a comparative study of the RE of light and heavy industries in China, and found the average RE of heavy industry was larger than that of light industry. In contrast to the above studies, a few scholars have also made efforts to investigate the economy-wide RE of China. For instance, Shao et al. [14] explored the economy-wide RE of China based on the time series data of 1954–2010, and the results indicated that the national average RE was 47.24% before 1978, and 37.32% after 1978. Zhang and Lin Lawell [36] calculated the macroeconomic RE of China during the period of 1991–2009, and found that the national average RE was −0.1421. Notably, studies of the economy-wide RE of China are relatively rare and the sizes of the RE are still not consistent. Considering the vast territory, resource endowment, and economic development differences in China, it is still necessary to investigate the economy-wide RE at the sub-national level for a deeper understanding of the RE. This will be helpful for providing policymakers with new insights to formulate specific measures to control the regional RE.

2.2. Research on the Determinants of CO_2 Emissions

As a result of global warming, carbon reduction has become the primary task to deal with climate change. Many scholars have explored the drivers of CO_2 emissions in terms of different aspects, such as economic growth, energy structure, urbanization, and trade openness. More specifically, the economic growth–CO_2 nexus, which is known as the environmental Kuznets curve (EKC), has been examined extensively in the existing research. For example, by employing the ARDL approach on a panel dataset from 1971 to 2011, Shahbaz et al. [37] investigated the EKC hypothesis for Malaysia and found that there is significant inverted-"U"-type relationship between economic growth and CO_2 emissions. This relationship was also confirmed by Esteve and Tamarit [38], Farhani et al. [16], Haisheng et al. [39], Iwata et al. [40], and Plassmann and Khanna [41]. Contrarily, some studies found little evidence supporting the EKC hypothesis. For instance, Zilio and Recalde [42] investigated the EKC hypothesis for the case of Latin America and the Caribbean for the period of 1970–2007, and found no support for this hypothesis. Based on the Engle–Granger test, Day and Grafton [43] also found little evidence for the validity of the EKC hypothesis for Canada. Notably, the nexus between economic growth and carbon CO_2 emissions is still controversial. Moreover, studies have emphasized the important role of the energy structure on CO_2 emissions. Specifically, by analyzing China's energy consumption structure over the period 1980–2006, Feng et al. [44] suggested that reducing the proportion of fossil energy in total energy consumption and transforming to clean energy can effectively mitigate carbon emissions. This conclusion was confirmed by Xu et al. [45] and Wang et al. [46].

Furthermore, a significant amount of work has been undertaken to examine the relationship between urbanization and CO_2 emissions, since the development of the urban economy requires sufficient energy input. Empirical results vary between studies, which have presented various views on the urbanization–CO_2 emissions nexus. For instance, using a sample of developing countries over the period 1975–2003, Martínez-Zarzoso and Maruotti [47] examined the relationship between urbanization and CO_2 emissions, and the research results indicate that there is an inverted-U-shaped relationship between urbanization and CO_2 emissions. Contrarily, Shahbaz et al. [48] identified a significant U-shaped urbanization–CO_2 emissions nexus for the case of Malaysia over the period of

1970–2011. In addition, Fan et al. [49] found a negative relationship between urbanization and CO_2 emissions for the sample of developing countries, and Liddle and Lung [50] found a positive insignificant relationship between urbanization and CO_2 emissions for the developed countries. In summary, the results regarding the relationship between urbanization and CO_2 emissions have not been conclusive. In addition, scholars also examined the relationship between trade openness and CO_2 emissions. Specifically, Mutascu [51] noted a one-way direction of causality from trade openness to carbon emissions in France over the period 1960–2013. Conversely, Shahbaz et al. [15] identified one-way causality running from CO_2 emissions to trade openness in China over the period 1970–2012. Furthermore, some studies have also detected two-way causality [52,53]. Notably, the trade openness–CO_2 nexus is still controversial within the literature. Furthermore, scholars also examined other influencing factors of CO_2 emissions. For example, the research results of Wójcik-Jurkiewicz et al. [54] and Drożdż et al. [55] identified significant roles of knowledge diffusion and public perception on decarbonization in Poland. In conclusion, to date, many studies have explored the drivers of CO_2 emissions in terms of various aspects; however, very few studies have systematically examined the potential impacts of the RE on CO_2 emissions, especially for the case of China. In the context of a low-carbon economy, it is necessary to systematically explore the extent to which the RE influences CO_2 emissions.

3. Materials and Methods

3.1. Measurement Procedure for Rebound Effect

As defined by Saunders [56], the rebound effect is:

$$RE = 1 + \eta \tag{1}$$

where $\eta = \frac{dlnE}{dlnDEPI}$ (E is the energy consumption, $DEPI$ denotes energy efficiency), which represents the elasticity of energy consumption to the energy efficiency. We can obtain the RE by estimating η.

We assumed that the optimal energy consumption of an enterprise is influenced by its output level, energy price, and energy efficiency. Following the work of Yan et al. [23] and Adetutu et al. [11], we constructed an optimal energy consumption function as follows:

$$lnE_{it}^* = g(lnP_{it}, lnY_{it}, lnDEPI_{it}) + \nu_i + \mu_{it} \tag{2}$$

where E_{it}^* represents optimal energy consumption, and P_{it}, Y_{it}, and $DEPI_{it}$ represent energy prices, real GDP, and energy efficiency, respectively. ν_{it} and μ_{it} are the constant term and the disturbance term, respectively.

For a given improvement in energy efficiency, enterprises require a certain amount of time to adjust their energy use. Therefore, we also considered the actual energy consumption in the process of dynamic adjustment:

$$nE_{it} - lnE_{i,t-1} = (1 - \sigma)(lnE_{it}^* - lnE_{i,t-1}) \tag{3}$$

where E_{it} represents the actual energy consumption, and $(1 - \sigma)$ is the adjustment proportion. Combining Equations (2) and (3), we obtained:

$$lnE_{it} = \sigma lnE_{i,t-1} + (1 - \sigma)g(lnP_{it}, lnY_{it}, lnDEPI_{it}) + \alpha_i + \pi_{it} \tag{4}$$

where $\alpha_i = (1 - \sigma)\nu_i$, $\pi_{it} = (1 - \sigma)\mu_{it}$. By performing the second-order Taylor expansion on $g(lnP_{it}, lnY_{it}, lnDEPI_{it})$, we obtained:

$$\begin{aligned}
lnE_{it} = &\sigma lnE_{i,t-1} + \beta_1 lnP_{it} + \beta_2 lnY_{it} + \beta_3 lnDEPI_{it} \\
&+ \tfrac{\beta_4}{2} lnP_{it} lnDEPI_{it} + \tfrac{\beta_5}{2} lnY_{it} lnDEPI_{it} + \tfrac{\beta_6}{2} lnP_{it} lnY_{it} \\
&+ \tfrac{\beta_7}{2} [lnP_{it}]^2 + \tfrac{\beta_8}{2} [lnY_{it}]^2 + \tfrac{\beta_9}{2} [lnDEPI_{it}]^2 + \alpha_i + \pi_{it}
\end{aligned} \tag{5}$$

According to the estimation parameters of Equation (5), we calculated the short- and long-run efficiency elasticity as follows:

$$\text{Short-run}: \eta_{SR}^{E} = \frac{dlnE_{it}}{dlnDEPI_{it}} = \beta_3 + \frac{\beta_4}{2}lnP_{it} + \frac{\beta_5}{2}lnY_{it} + \beta_9 lnDEPI_{it} \tag{6}$$

$$\text{Long-run}: \eta_{LR}^{E} = \beta_3 + \frac{\frac{\beta_4}{2}lnP_{it} + \frac{\beta_5}{2}lnY_{it} + \beta_9 lnDEPI_{it}}{1 - \sigma} \tag{7}$$

Therefore, the RE in the short and long run can be obtained according to Equations (6) and (7):

$$\text{Short-run RE} = 1 + \eta_{SR}^{E} \tag{8}$$

$$\text{Long-run RE} = 1 + \eta_{LR}^{E} \tag{9}$$

Notably, we selected the price index of fuels ($P_{2000} = 100$) as the proxy for the energy price due to the absence of energy price data; this was derived from the CSY (2018) [57]. The data on energy efficiency were obtained from the calculation results in Section 3.2. The data on energy consumption were taken from the CESY (2018) [58], and the GDP data originated from the CSY (2018) [57], and are deflated based on the 2000 constant price.

3.2. Measurement Procedure for Energy Efficiency

To estimate efficiency elasticity (η), we first need to measure the energy efficiency level. To this end, we constructed a dynamic comprehensive energy efficiency indicator (*DEPI*) that fully considers various input factors and changes in energy technology progress. To calculate the *DEPI*, we first needed to evaluate the Shephard energy distance function, which identifies the extent to which energy input factors decrease when other input factors remain the same in the production possibility set. We assumed that each decision-making unit, i.e., each province of China ($DMU_j, j = 1, 2, \ldots, 30$), yields the desired output *GDP* (*Y*) based on the three inputs: capital (*K*), energy (*E*), and labor (*L*); where *K* is determined based on the perpetual inventory method using 2000 constant prices. *E* is determined using the provincial aggregate energy consumption. Each province's employee count at the end of the year represents *L*, and *Y* is measured by real *GDP* using 2000 constant prices. All data were derived from China's various statistical yearbooks. Following the work of Boyd and Pang [59] and Wu et al. [60], the Shephard energy distance function is expressed as:

$$lnD_E^t\left(K_j^t, L_j^t, E_j^t, Y_j^t\right) = f\left(lnK_j^t, lnL_j^t, lnE_j^t, lnY_j^t, t\right) + \eta_j + \nu_{jt} \tag{10}$$

where $f(\cdot)$ is an unknown function, η_j represents an unobserved individual effect, and ν_{jt} represents a random disturbance term. Using its second-order Taylor expansion, we approximated Equation (10) as follows:

$$\begin{aligned}
lnD_E^t\left(K_j^t, L_j^t, E_j^t, Y_j^t\right) = & \alpha_k lnK_j^t + \alpha_l lnL_j^t + \alpha_e lnE_j^t + \alpha_y lnY_j^t + \alpha_t t \\
& + \frac{\alpha_{kl}}{2}lnK_j^t lnL_j^t + \frac{\alpha_{ke}}{2}lnK_j^t lnE_j^t + \frac{\alpha_{ky}}{2}lnK_j^t lnY_j^t \\
& + \frac{\alpha_{kt}}{2}lnK_j^t t + \frac{\alpha_{le}}{2}lnL_j^t lnE_j^t + \frac{\alpha_{ly}}{2}lnL_j^t lnY_j^t + \frac{\alpha_{lt}}{2}lnL_j^t t \\
& + \frac{\alpha_{ey}}{2}lnE_j^t lnY_j^t + \frac{\alpha_{et}}{2}lnE_j^t t + \frac{\alpha_{yt}}{2}lnY_j^t t + \frac{\alpha_{kk}}{2}\left[lnK_j^t\right]^2 \\
& + \frac{\alpha_{ll}}{2}\left[lnL_j^t\right]^2 + \frac{\alpha_{ee}}{2}\left[lnE_j^t\right]^2 + \frac{\alpha_{yy}}{2}\left[lnY_j^t\right]^2 \\
& + \frac{\alpha_{tt}}{2}t^2 + \eta_j + \nu_{jt}
\end{aligned} \tag{11}$$

Due to the linear homogeneity of the Shephard energy distance function with respect to energy factor inputs, the following relationship exists:

$$lnD_E^t\left(K_j^t, L_j^t, E_j^t, Y_j^t\right) = lnD_E^t\left(K_j^t, L_j^t, 1, Y_j^t\right) + lnE_j^t \tag{12}$$

By combining Equations (11) and (12), we obtained:

$$
\begin{aligned}
-lnE_j^t = {}& \alpha_k lnK_j^t + \alpha_l lnL_j^t + \alpha_y lnY_j^t + \alpha_t t \\
& + \frac{\alpha_{kl}}{2} lnK_j^t lnL_j^t + \frac{\alpha_{ky}}{2} lnK_j^t lnY_j^t + \frac{\alpha_{kt}}{2} lnK_j^t t \\
& + \frac{\alpha_{ly}}{2} lnL_j^t lnY_j^t + \frac{\alpha_{lt}}{2} lnL_j^t t + \frac{\alpha_{yt}}{2} lnY_j^t t \\
& + \frac{\alpha_{kk}}{2} \left[lnK_j^t \right]^2 + \frac{\alpha_{ll}}{2} \left[lnL_j^t \right]^2 + \frac{\alpha_{yy}}{2} \left[lnY_j^t \right]^2 \\
& + \frac{\alpha_{tt}}{2} t^2 + \eta_j - \mu_{jt} + \nu_{jt}
\end{aligned}
\tag{13}
$$

where μ_{jt} represents the inefficiency of energy use, which follows $N^+\left(0, \sigma_\mu^2\right)$. Considering the stochastic frontier analysis (*SFA*) has obvious advantages in dealing with statistical noise and the heterogeneity of the reaction technology, we adopted the *SFA* method to estimate Equation (13). According to the parameter estimation results of Equation (13), we can estimate the static energy efficiency of each DMU_j using the following equation:

$$
Eff_{jt} = E\left[exp\left(-\mu_{jt}\right) \middle| \varepsilon_{jt} \right]
\tag{14}
$$

where $\varepsilon_{jt} = \nu_{jt} - \mu_{jt}$. Thus, the static energy efficiency change is calculated by the following equation:

$$
Effch_j^{t,t+1} = \frac{Eff_{j,t+1}}{Eff_{jt}}
\tag{15}
$$

Then, the change in energy technology progress is obtained by calculating the following equation:

$$
Tecch_j^{t,t+1} = \left[\begin{array}{c} exp\left(\alpha_t + \alpha_{tk}K_j^{t+1} + \alpha_{tl}L_j^{t+1} + \alpha_{ty}Y_j^{t+1} + \alpha_{tt}(t+1)\right) \\ \times exp\left(\alpha_t + \alpha_{tk}K_j^t + \alpha_{tl}L_j^t + \alpha_{ty}Y_j^t + \alpha_{tt}t\right) \end{array} \right]^{1/2}
\tag{16}
$$

Finally, the product of $Effch_j^{t,t+1}$ and $Tecch_j^{t,t+1}$ is the dynamic comprehensive energy efficiency (*DEPI*), which is presented in Figure 1.

3.3. Econometric Model

After evaluating the RE, we empirically explored the potential impacts of the RE in the short and long term on CO$_2$ emissions, and determined the validity of the CO$_2$–EKC (environmental Kuznets curve) hypothesis. To avoid false regression problems, we considered the following control variables: economic development level, energy structure, urbanization, and trade openness. Thus, we constructed the CO$_2$–EKC model as follows:

$$
\begin{aligned}
lnCO_{2it} = {}& \beta_0 + \beta_1 lnCO_{2i,t-1} + \beta_2 lnSRE_{it} + \beta_3 lnPgdp_{it} + \beta_4 (lnPgdp_{it})^2 \\
& + \beta_5 lnENS_{it} + \beta_6 lnUrb_{it} + \beta_7 lnTra_{it} + \mu_{it}
\end{aligned}
\tag{17}
$$

$$
\begin{aligned}
lnCO_{2it} = {}& \beta_0 + \beta_1 lnCO_{2i,t-1} + \beta_2 lnLRE_{it} + \beta_3 lnPgdp_{it} + \beta_4 (lnPgdp_{it})^2 \\
& + \beta_5 lnENS_{it} + \beta_6 lnUrb_{it} + \beta_7 lnTra_{it} + \mu_{it}
\end{aligned}
\tag{18}
$$

where CO$_2$ represents the CO$_2$ emissions of each province. *SRE* and *LRE* represent the short-run and long-run RE, respectively. *Pgdp* represents the economic development level, and *Tra* represents trade openness. *ENS* and *Urb* represent the energy structure and urbanization, respectively. $\beta_1 - \beta_7$ are the parameters to be estimated by the model. β_0 is the constant term, and μ_{it} represents the random disturbance term.

3.4. Variable Selection and Data Sources

A panel dataset of 30 provinces in China, from 2001 to 2017, was used in this study for empirical analysis. The sample excluded Tibet, Taiwan, Hong Kong, and Macao because of data unavailability. The data on CO_2 emissions were taken from the China Emission Accounts and Database [8]. The RE data for the key explanatory variables (represented by *SRE* and *LRE*, respectively), in the short and long run, were derived from the calculation results in Section 4.1.

Regarding the control variables, economic development (*Pgdp*) was measured by *GDP* per capita, energy structure (*ENS*) was measured by coal consumption as a percentage of total energy consumption, urbanization (*Urb*) was calculated by the ratio of permanent urban population to total population, and trade openness (*Tra*) was presented as the ratio of net trade imports and exports to aggregate *GDP*. All data were derived from various statistical yearbooks of China, which are reported in Table A1 in Appendix A. Detailed descriptive statistics are provided in Table 1 for all of the above variables.

Table 1. Descriptive statistics of each variable.

Variables	Obs.	Mean	Std.	Min	Max
$lnCO_2$	510	5.231302	0.9563584	−0.0725707	7.347306
lnSRE	510	4.493737	0.1548966	3.781551	4.816922
lnLRE	510	4.343329	0.1830008	3.352524	4.612049
lnENS	510	3.628914	0.3499347	2.471484	3.971046
lnPgdp	510	8.987297	1.097089	5.704116	11.42572
lnUrb	510	3.881446	0.2867018	3.136033	4.516998
lnTra	510	1.25809	0.8342213	−0.4123573	4.315205

Note: Std. indicates the standard deviation; Min and Max represent minimum and maximum, respectively.

4. Results

4.1. Rebound Effect Estimation Results

We used the system generalized method of moments (SYS-GMM) to evaluate the parameters in Equation (5), considering the dynamic feature of this model. The results are reported in Table 2. To ensure the estimation results were robust, the differential generalized method of moments (D-GMM) estimation results are also reported. The AR test showed no second-order autocorrelation existed, as shown in Table 1. Based on the Sargan test results, all instrumental variables selected by the model satisfied the exogenous conditions, which implies the validity of all instrumental variables. Moreover, compared to the D-GMM method, the estimation results of the SYS-GMM approach were significantly improved, which supports the appropriateness of utilizing the SYS-GMM method for this model.

Table 2. Parameter estimation results.

Variables	Parameter	D-GMM		SYS-GMM	
		Value	Std.	Value	Std.
L.lnE	σ	0.8507 ***	0.0101	0.4302 ***	0.0143
lnP	β_1	0.1076 ***	0.0283	0.2038 ***	0.0341
lnY	β_2	0.2245 ***	0.0172	0.2988 ***	0.0152
lnDEPI	β_3	−0.0591 *	0.1805	−0.1493 ***	0.0249
$0.5 \times (lnP{\cdot}lnDEPI)$	β_4	0.1386 *	0.1633	0.0789 **	0.0442
$0.5 \times (lnDEPI{\cdot}lnY)$	β_5	0.0957 ***	0.0184	0.1067 **	0.0814
$0.5 \times (lnP{\cdot}lnY)$	β_6	0.1104 *	0.0639	−0.0780 ***	0.0204
$0.5 \times [lnP]^2$	β_7	−0.1926	0.1868	−0.3167 **	0.0197
$0.5 \times [lnY]^2$	β_8	−0.0081	0.1445	−0.0129 ***	0.0133
$0.5 \times [lnDEPI]^2$	β_9	−0.0936 ***	0.0667	−0.1467 ***	0.0025
_Cons	α	−0.1452 ***	0.0538	−0.3877 ***	0.0981
AR (1)		0.0251		0.0013	
AR (2)		0.1476		0.1885	
Sargan test		0.9841		1.000	
Obs.		448		478	

Note: ***, **, * means the parameters are significant at the levels of 1%, 5%, and 10%, respectively; Std. represents standard errors.

Based on the parameter estimation results in Table 1, the RE value of each province was calculated in the short and long term. Figure 4 presents the average value of the RE in each province from 2001 to 2017. As clearly shown in Figure 4, most of the provinces experienced a partial RE during this period, but some provinces, such as Guangxi and Henan, experienced a backfire effect. The average RE across the nation was 90.47% in the short term, and 78.17% in the long term.
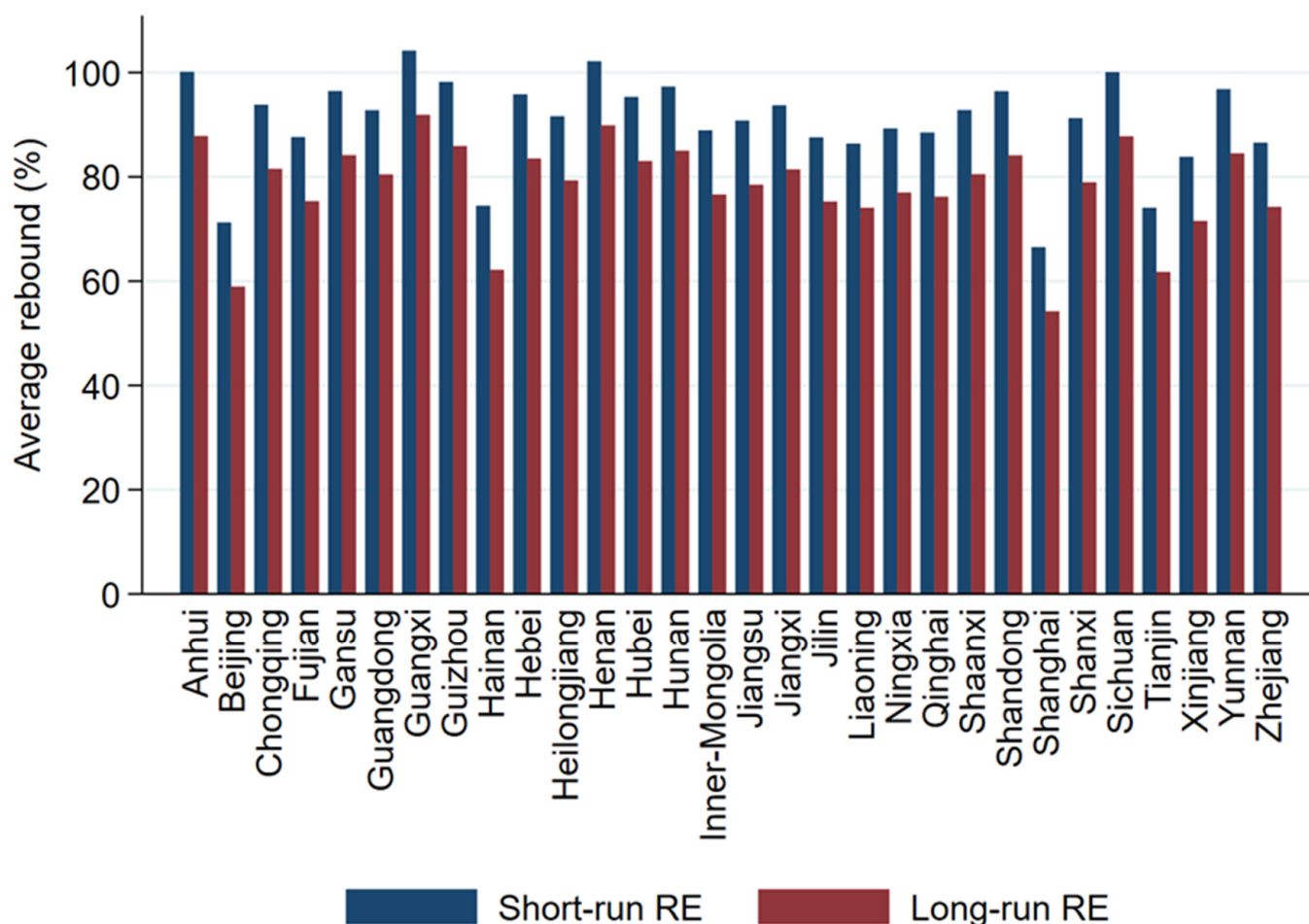
Figure 4. Average RE of 30 Chinese provinces in the short and long run.

To clearly identify the evolution track of China's RE, we drew spatial distribution maps of China's RE, both in the short and long run, for 2001, 2006, 2012, and 2017, which are presented in Figure 5. Notably, two interesting phenomena attracted our attention from Figure 5. First, the RE was greater in the short run than in the long run. This may be because, in the context of low energy prices and marketization in China, energy prices have not adjusted in the short term to reflect the improvements in energy efficiency.

Therefore, improving energy efficiency will greatly stimulate energy demand to a large extent in the short term, which leads to a steep discount of the potential energy savings from improved energy efficiency. In the long run, energy prices may adjust to some extent; in addition, knowledge accumulation and increased awareness of environmental conservation among economic agents, and environmental regulation policies, will encourage end-users to make more efficient use of energy. As a result, the energy-saving benefits of improved energy efficiency will be gradually realized in the long run.
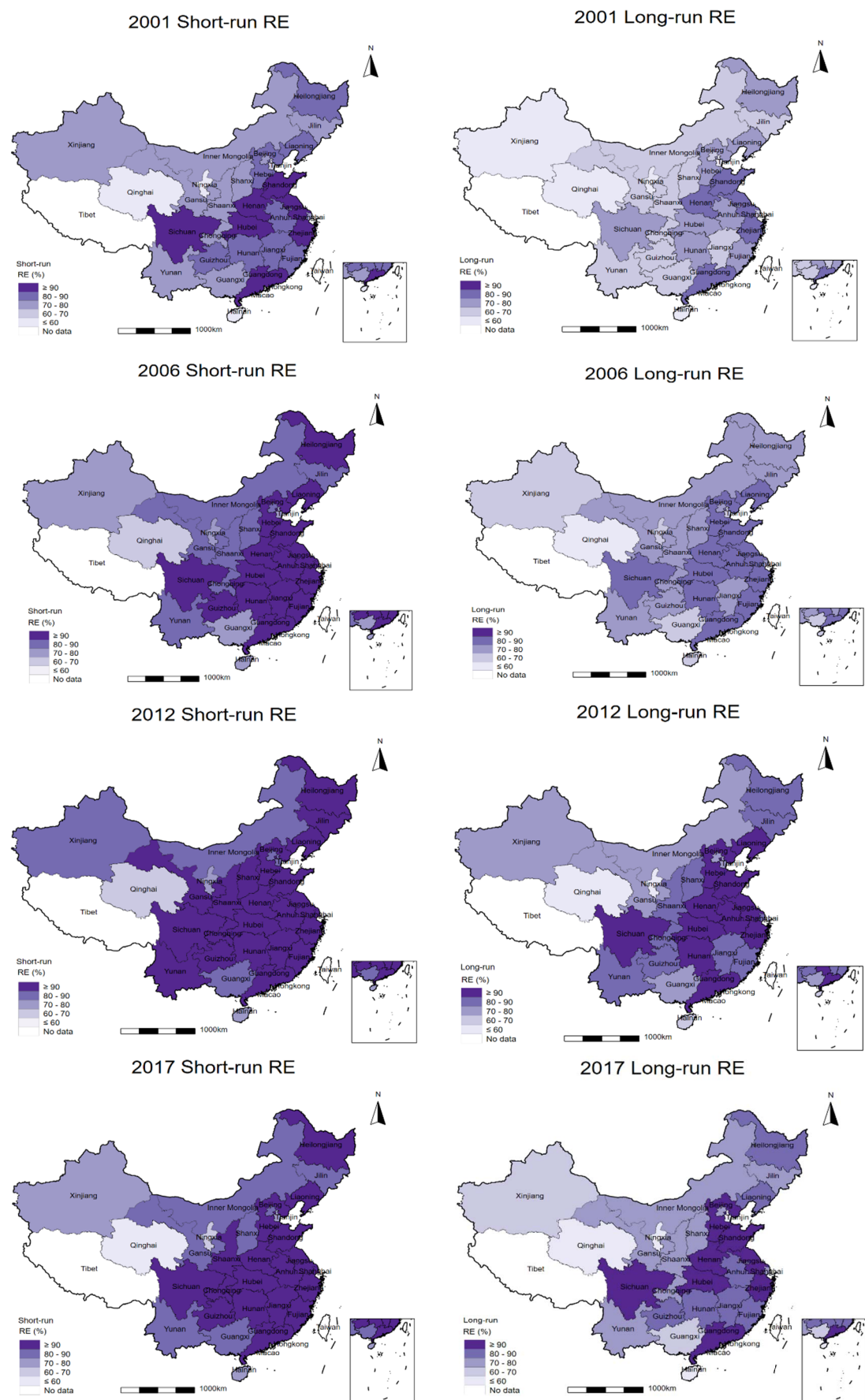
Figure 5. Spatial distribution of China's short-run and long-run RE.

Second, Figure 5 shows that most of the high-RE provinces are located in the central and eastern regions of the country. According to Orea et al. [61], energy prices and income levels are the main factors affecting the energy rebound. Because energy prices are relatively low and market oriented in China, this finding can be discussed further with consideration of regional economic development differences. Eastern China is a developed region having the highest GDP per capita (CNY 20,660.34 billion), whereas that of the central region is moderate (CNY 11,739.36 billion GDP per capita) and the western region is relatively poor (CNY 6952.39 billion GDP per capita) [62]. In light of the fact that rapid industrialization and urbanization are taking place in China at present, there are still no signs of a decoupling between regional economic growth and energy consumption. Due to the high income levels and large economic scale in the eastern and central regions, their energy consumption demand is far greater than that in the poorer western regions. Therefore, the rapid improvement in energy efficiency in these regions (as shown in Figure 1) stimulates significant energy demand. In the sample period, the average energy consumption in the eastern and central regions reached 139.96 and 109.94 Mtce, respectively, whereas that of the western region was only 68.88 Mtce [7]. Correspondingly, as shown in Figure 1, energy efficiency improvements in the western region are not obvious, and energy efficiency even deteriorated in some provinces. Therefore, the RE in the western region is not obvious due to the low energy efficiency and poor income level.

4.2. Econometric Model Estimation Results

4.2.1. Cross-Sectional Dependence Test Results

Grossman and Krueger [63] noted that ignoring cross-sectional dependence within panel data will affect the credibility of the estimation results, which may result in inconsistent evaluation results. Therefore, it is essential to perform a cross-sectional dependence test before empirical analysis is conducted [64]. For this purpose, we employed the Pesaran cross-sectional dependence test [65], Breusch–Pagan Lagrange multiplier test [66], Friedman test [67], and Frees test [68] to identify whether cross-sectional dependence exists. Table 3 reports the test results, and shows that, at the 1% significance level, all four tests rejected the null hypothesis of no cross-sectional dependence. Therefore, it was necessary to take into account cross-sectional dependence when performing the empirical analysis in this study.

Table 3. Results of the cross-sectional dependence test.

Test	Statistics	Prob.
Pesaran CD test	93.612 ***	0.0000
Breusch–Pagan LM test	491.382 ***	0.0000
Friedman test	57.898 ***	0.0000
Frees test	4.898 ***	0.0000

Note: *** indicates statistical significance at 1%.

4.2.2. Panel Unit Root Test Results

A stationarity check is necessary for each variable before empirical analysis is conducted to avoid invalid regression problems. We utilized the CIPS tests and Pesaran CADF test [69], which permit the existence of cross-sectional dependence [70], to detect stationarity for each variable in this study. Table 4 reports the results of the above two tests, and shows that only some variables (e.g., CO_2, *ENS*, and *Pgdp*) are significant at the tested level. Therefore, we took the first-order difference for each variable. After taking the first-order difference, each variable rejected the null hypothesis (existence of a unit root) at the 1% significance level. Thus, each variable should be transformed into a variable having an order of one in the subsequent estimation procedure.

Table 4. Panel unit root test results.

Variable	Level		1st Difference	
	Intercept	Intercept and Trend	Intercept	Intercept and Trend
	Pesaran CIPS test			
$lnCO_2$	−2.631 ***	−2.940 ***	−4.199 ***	−4.270 ***
$lnSRE$	−2.053	−2.567	−3.563 ***	−3.643 ***
$lnLRE$	−1.905	−2.558	−3.584 ***	−3.630 ***
$lnENS$	−2.104 *	−2.442 **	−3.874 ***	−3.787 ***
$lnPgdp$	−2.489 **	−2.790 **	−2.605 ***	−3.220 ***
$lnUrb$	−1.641	−1.759	−2.587 ***	−2.828 ***
$lnTra$	−1.992	−2.780 **	−3.900 ***	−3.866 ***
	Pesaran CADF test			
$lnCO_2$	−2.533 ***	−3.153 ***	−3.459 ***	−3.533 ***
$lnSRE$	−1.921	−2.491	−2.876 ***	−3.123 ***
$lnLRE$	−1.924	−2.478	−2.877 ***	−3.104 ***
$lnENS$	−2.080 **	−2.575 *	−3.122 ***	−2.958 ***
$lnPgdp$	−2.073 **	−2.439 **	−3.300 ***	−3.726 ***
$lnUrb$	−1.817	−1.981	−2.481 ***	−2.574 ***
$lnTra$	−1.334	−2.175	−2.097 ***	−3.768 ***

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

4.2.3. Benchmark Regression

We first drew the correlation plot between the RE and CO_2 emissions, as presented in Figure 6, which shows that the RE measures (*lnSRE* and *lnLRE*) are positively correlated with CO_2 emissions. Their goodness of fit values (R^2), however, are only 0.2789 and 0.2854, respectively. Therefore, more accurate and efficient methods are needed in a further step to fully understand the impact of the RE on CO_2 emissions.
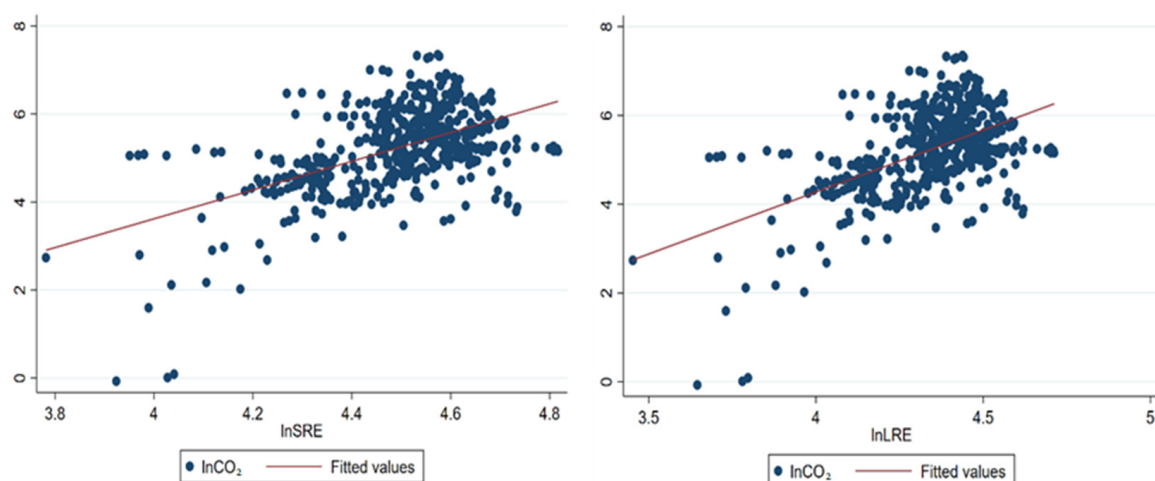

Figure 6. Correlation diagram between RE and CO_2 emissions.

The GMM method is more suitable for dynamic panel models (Equations (17) and (18)) considering their dynamic features, because it can solve the endogeneity problem by introducing reasonable instruments, thus effectively improving estimation results [71]. Specifically, the system GMM (SYS-GMM) approach can be used to introduce more effective instrumental variables, and to simultaneously estimate the level and difference equations, which improves the validity of estimation results compared with the difference GMM (D-GMM) method [72]. Therefore, we adopted the SYS-GMM estimation method as a benchmark and report the D-GMM estimation results due to their robustness. Table 5 presents the results; the AR test results indicate that second-order autocorrelation does not

exist. All of the instrumental variables used in the model meet the exogenous conditions based on the results of the Sargan test, and thus are valid.

Table 5. Results of modeling the impact of RE on CO_2 emissions.

Variables	Short-Run RE		Long-Run RE	
	SYS-GMM	**D-GMM**	**SYS-GMM**	**D-GMM**
$lnCO_{2,t-1}$	0.333 ***	0.289 ***	0.331 ***	0.286 ***
	(19.32)	(16.06)	(19.14)	(15.87)
$lnSRE$	0.818 ***	0.543 ***		
	(5.57)	(4.38)		
$lnLRE$			0.695 ***	0.493 ***
			(5.53)	(4.66)
$lnENS$	0.805 ***	0.745 ***	0.843 ***	0.726 ***
	(14.55)	(16.85)	(14.48)	(16.85)
$lnPgdp$	0.645 ***	0.424 ***	0.543 ***	0.705 ***
	(8.87)	(5.96)	(4.84)	(5.99)
$lnPgdp^2$	−0.025 **	−0.020 *	−0.027 **	−0.023 **
	(−2.06)	(−1.72)	(−2.18)	(−2.07)
$lnUrb$	0.303 **	0.288 ***	0.341 **	0.311 ***
	(2.28)	(8.23)	(2.10)	(8.27)
$lnTra$	0.045 ***	0.038 ***	0.052 ***	0.041 ***
	(6.15)	(5.75)	(6.16)	(5.83)
_Cons	−2.01 ***	−3.32 ***	−2.92 ***	−2.23 ***
	(−12.53)	(−9.40)	(−11.68)	(−9.11)
AR (1)	0.010	0.011	0.007	0.007
AR (2)	0.461	0.498	0.462	0.469
Sargan test	0.996	0.999	0.998	1.000
Obs.	480	450	480	450

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; z value in parentheses.

As can be seen in Table 5, both the short-run and long-run RE have significant positive impacts on CO_2 emissions in China. Specifically, a 1% increase in the short-run RE leads to an increase in CO_2 emissions of 0.818%, whereas a 1% increase in the long-run RE causes CO_2 emissions to rise by approximately 0.695%. These results warrant great concern. The increasingly significant RE poses a potential challenge to the carbon reduction goals. To strengthen environmental protection and reduce greenhouse gas emissions, the central government of China proposed a "double control policy" in October 2015, which specifically aimed to control the total energy consumption and energy intensity. Improving energy efficiency is the key to reducing energy intensity and, subsequently, reducing total energy consumption. Driven by the strong national energy policy, China's energy efficiency has gradually improved, as shown in Figure 1. However, the results of this study imply that the existence of a large RE is a potential challenge to achieving the energy-saving objectives outlined in the policies by solely relying on improved energy efficiency. Due to China's vast territory, large population, and unbalanced regional development, many provinces are still at a stage of rapid industrialization and urbanization, which requires enormous energy input. Therefore, the rapid improvement in energy efficiency greatly stimulates energy consumption in the context of low energy prices and marketization in China, which results in more CO_2 emissions.

Regarding the control variables, there is a significant positive effect of the energy structure on CO_2 emissions, which indicates the urgency of the energy structure adjustment. The coefficient of per capita income is positive, but its quadratic term is negative; this implies the existence of an inverted-U-shaped nexus between per capita income and CO_2 emissions, which proves the validity of the CO_2–EKC hypothesis. Saboori et al. [73] and Dong et al. [74] also came to the same conclusions. In addition, urbanization presents a significantly positive effect on CO_2 emissions. In light of China's rapid urbanization, many rural laborers are migrating to cities, which creates demand for services such as housing

and medical services. These additional demands inevitably propel energy consumption, and thus promote CO_2 emissions. Finally, a positive estimate of trade openness implies that trade openness positively impacts China's CO_2 emissions. The possible reason for this is that increasing domestic and international trade may result in increased CO_2 emissions due to the flow of factors between regions [75].

4.2.4. Robustness Checks

We performed a robustness test by introducing a new dependent variable, per capita CO_2 emissions (denoted as PCO_2), to determine the validity and reliability of the benchmark regression results. The test results from the SYS-GMM and D-GMM approaches are presented in Table 6. A comparison of the estimation results in Tables 5 and 6 indicates that the core explanatory variables, e.g., short-run RE (*lnSRE*) and long-run RE (*lnLRE*), in addition to the other control variables, exhibit consistency, both in terms of coefficient size and statistical significance. This indicates the reliability and credibility of the benchmark regression results presented in Section 4.2.3.

Table 6. Robustness test results using an alternative variable.

| Variables	Short-Run RE		Long-Run RE	
	SYS-GMM	**D-GMM**	**SYS-GMM**	**D-GMM**
$lnPCO_{2,t-1}$	0.345 ***	0.298 ***	0.336 ***	0.295 ***
	(23.65)	(17.12)	(19.88)	(16.85)
lnSRE	0.756 ***	0.502 ***		
	(5.93)	(3.94)		
lnLRE			0.630 ***	0.475 ***
			(8.21)	(4.25)
lnENS	0.781 ***	0.639 ***	0.714 ***	0.688 ***
	(23.22)	(29.50)	(22.66)	(29.26)
lnPgdp	0.603 ***	0.571 ***	0.718 ***	0.625 ***
	(4.61)	(6.60)	(5.85)	(5.99)
$lnPgdp^2$	−0.023 **	−0.017 ***	−0.028 ***	−0.021 ***
	(−2.01)	(−2.79)	(−3.12)	(−5.07)
lnUrb	0.318 **	0.262 ***	0.325 **	0.301 ***
	(2.22)	(8.93)	(2.09)	(12.82)
lnTra	0.040 ***	0.048 ***	0.057 ***	0.044 ***
	(4.78)	(5.01)	(3.84)	(8.29)
_Cons	−3.71 ***	−3.58 ***	−2.11 ***	−5.25 ***
	(−5.06)	(−10.24)	(−9.73)	(−27.66)
AR (1)	0.001	0.010	0.011	0.006
AR (2)	0.483	0.423	0.503	0.539
Sargan test	1.000	0.955	0.996	1.000
Obs.	480	450	480	450

Note: ***, ** indicate statistical significance at the 1% and 5% levels, respectively; z value in parentheses.

5. Discussion

5.1. Regional Heterogeneity Analysis

The distribution map of the RE and CO_2 emissions exhibits obvious regional heterogeneity among different regions in China, as displayed in Figures 1 and 3. Therefore, to understand whether the impacts of the RE on CO_2 emissions differ across various regions, we grouped the whole sample based on the average value of the RE and the CO_2 emissions of each province. Considering that the spatial distributions of short-run and long-run RE exhibit similar characteristics (as shown in Figure 5), the mean value of the two RE measures was utilized to represent the total RE for the groups. Therefore, the full sample was categorized into four groups: (1) the high-RE region, which includes the provinces having an RE greater than the national average; (2) the low-RE region, which includes the provinces having an RE lower than the national average; (3) the high-emission region, which includes the provinces having CO_2 emissions higher than the national average;

(4) and the low-emission region, which includes the provinces having CO_2 emissions lower than the national average. The specific provinces in each group are presented in Figure 7.
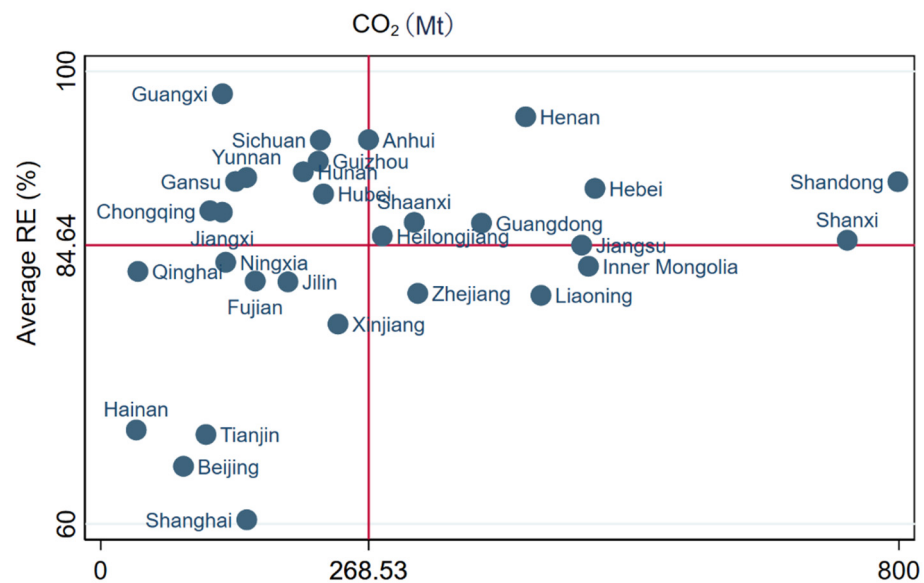
Figure 7. Group division based on the RE and CO_2 emissions of China's 30 provinces.

Accordingly, on the basis of the SYS-GMM method, we explored the impacts of the RE on CO_2 emissions across the four regions, and the results are reported in Table 7. It can be seen from this table that there are significant regional differences in the impact of the RE on CO_2 emissions. In further detail, the RE positively affects CO_2 emissions in both the high-emission and low-emission regions at the 1% significance level. Specifically, a 1% increase in the RE will lead to increases in CO_2 emissions of approximately 0.655% in the high-emission region and 0.332% in the low-emission region. Notably, this positive impact in the high-emission region is greater than that in the low-emission region. A possible reason for this may be that, in high-emission regions, provinces such as Shanxi and Shandong are dominated by large-scale heavy industry, and urbanization is rapidly developing, both of which require great amounts of energy. Therefore, improved energy efficiency (as shown in Figure 1) increased energy consumption in these areas, resulting in a large RE (as shown in Figure 4), which caused an increase in CO_2 emissions. In summary, reducing the RE will be conducive to mitigating CO_2 emissions in both high-emission regions and low-emission regions in China. Furthermore, there is more scope for emissions reductions from the perspective of the energy rebound, especially for high-emission regions.

In addition, the RE still contributes significantly to CO_2 emissions, in both the high-RE and low-RE regions. More specifically, a 1% increase in the RE will lead to increments in CO_2 of approximately 0.731% in the high-RE region and 0.406% in the low-RE region. Provinces in the high-RE region, such as Guangxi and Henan, are currently experiencing rapid industrialization and urbanization, and thus the energy demand of these areas is still increasing. Therefore, improving energy efficiency in these areas leads to a significant increment in energy consumption, which subsequently results in large energy rebounds and carbon emissions. As shown in Figure 4, none of the provinces showed excellent energy savings, but all showed partial rebounds, and some provinces even experienced the backfire effect. This indicates that the potential energy savings resulting from the energy efficiency improvement are offset by the additional new energy demand, which leads to faster carbon emissions.

Table 7. Results of the regional heterogeneity analysis.

Variables	High-Emission Region	Low-Emission Region	High-RE Region	Low-RE Region
$lnCO_{2,t-1}$	0.749 ***	0.308 ***	0.422 ***	0.301 **
	(6.09)	(5.54)	(3.56)	(2.21)
$lnRE$	0.655 ***	0.232 ***	0.731 ***	0.356 ***
	(2.94)	(3.87)	(4.06)	(5.37)
$lnENS$	0.737 ***	0.401 ***	0.505 ***	0.427 ***
	(2.71)	(2.93)	(8.12)	(7.91)
$lnPgdp$	0.681 ***	0.307 **	0.755 ***	0.362 *
	(3.26)	(2.46)	(5.33)	(1.73)
$lnPgdp^2$	−0.018 *	−0.020 ***	−0.013	−0.027 **
	(−1.23)	(−3.08)	(−1.01)	(−2.00)
$lnUrb$	0.438 ***	0.211 **	0.037 ***	0.028 **
	(3.19)	(2.30)	(5.85)	(2.35)
$lnTra$	0.053 ***	0.040 **	0.043 ***	0.032 ***
	(4.36)	(2.18)	(5.61)	(3.39)
$\_Cons$	−1.055 ***	−1.741 ***	−0.599 ***	−3.63 ***
	(−10.12)	(−9.90)	(−8.21)	(−7.28)
AR (1)	0.002	0.001	0.021	0.011
AR (2)	0.3595	0.460	0.759	0.673
Sargan test	1.000	0.922	0.913	0.945
Obs.	272	208	272	208

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; z value in parentheses.

5.2. Asymmetric Analysis

We examined the overall impact of the RE on CO_2 emissions on the basis of the SYS-GMM technique. To explore the asymmetric impacts of the RE on CO_2 emissions, we re-estimated the benchmark models (Equations (17) and (18)) based on the two-step quantile regression method; these results are reported in Table 8. We also plotted the changing track of each variable's coefficients at the 10th, 25th, 50th, 75th, and 90th quantile levels, as shown in Figure 8.

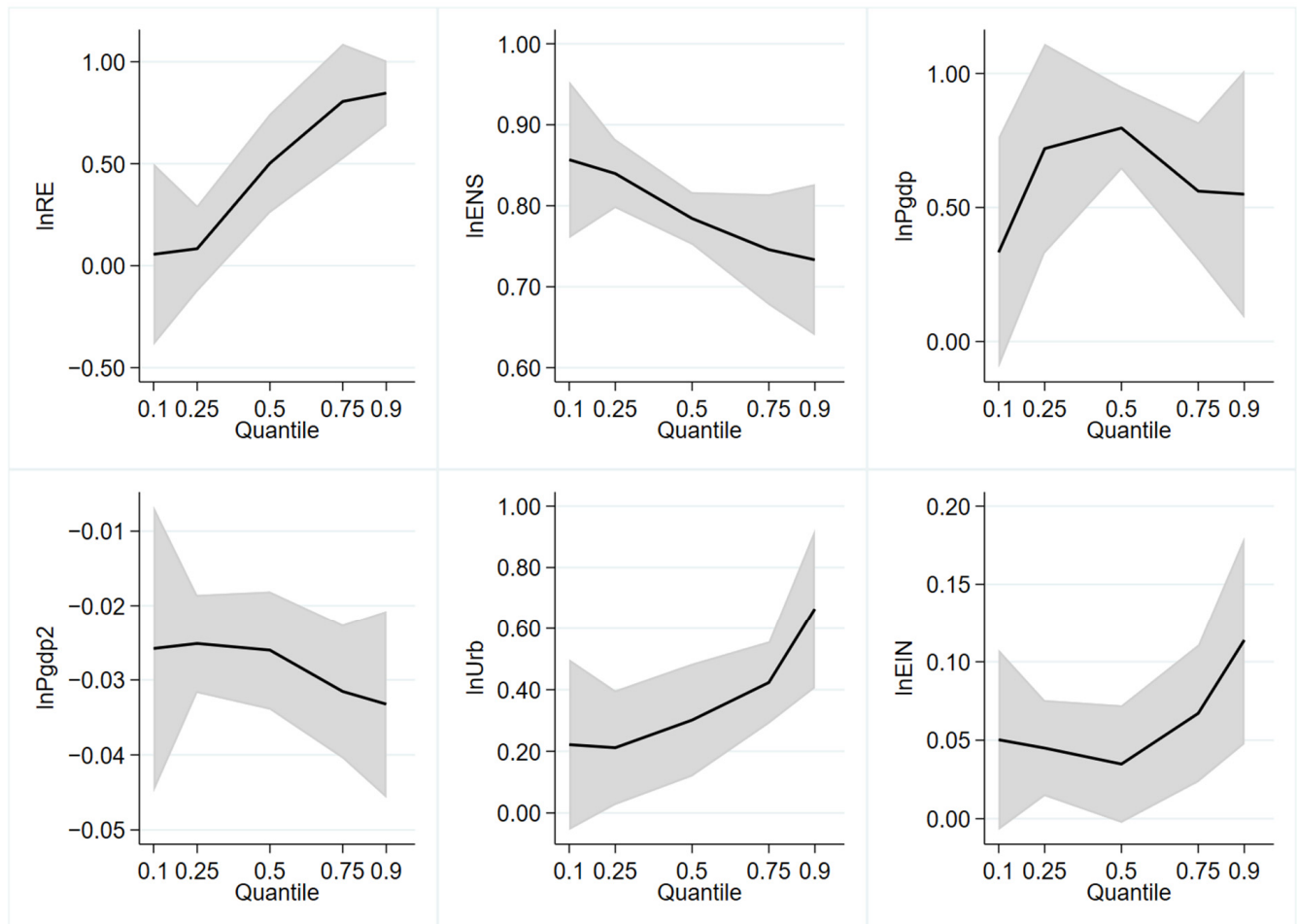**Table 8.** Two-step quantile regression results.

	Dependent variable: $lnCO_2$				
Variable	10th	25th	50th	75th	90th
$lnRE$	0.056	0.083	0.503 ***	0.805 ***	0.846 ***
	(0.29)	(0.73)	(4.47)	(7.49)	(7.83)
$lnENS$	0.856 ***	0.839 ***	0.784 ***	0.745 ***	0.733 ***
	(16.41)	(18.99)	(32.10)	(21.61)	(18.68)
$lnPgdp$	0.332	0.719 ***	0.796 ***	0.561 ***	0.549 **
	(1.25)	(8.27)	(8.22)	(3.86)	(2.34)
$lnPgdp^2$	−0.026 **	−0.025 ***	−0.026 ***	−0.031 ***	−0.033 ***
	(−2.35)	(−5.33)	(−5.85)	(−5.52)	(−5.45)
$lnUrb$	0.221 *	0.211 **	0.301 ***	0.423 ***	0.664 ***
	(1.72)	(2.36)	(3.46)	(7.09)	(5.93)
$lnTra$	0.050 *	0.045 ***	0.034 **	0.067 **	0.113 **
	(1.88)	(3.23)	(2.41)	(2.07)	(2.27)
$\_Cons$	−5.240 ***	−4.753 ***	−3.601 ***	−2.621 ***	−2.059 ***
	(−19.21)	(−10.41)	(−13.30)	(−7.50)	(−7.74)
R-squared	0.6933	0.6795	0.6755	0.6633	0.6280

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; t value in parentheses.

As shown in Table 8, the influences of different variables on CO_2 emissions exhibit significant heterogeneity. More specifically, at the 10th and 25th quantiles, the coefficient of the RE is not significant, but becomes significant at higher quantiles with an obvious increase in coefficient size. This implies that the marginal decrease in the RE in the provinces located at higher quantiles (i.e., 50th, 75th, and 90th) promotes a greater CO_2 reduction

than that in the provinces located at the lower quantiles, which supports the findings of the regional heterogeneity analysis in Section 5.1. In terms of the control variables, an inverted-U-type nexus still exists between per capita income and CO_2 emissions, except at the 10th quantile. The coefficients of energy structure (*lnENS*), urbanization (*lnUrb*), and trade openness (*lnTra*) at all quantiles are statistically significant, and the signs are consistent with the benchmark estimation results, as discussed in Section 4.2.3. This indicates CO_2 emissions in China are significantly affected by energy structure, urbanization, and trade openness at all quantile levels.

Figure 8. Coefficient change for each variable in two-step quantile regression.

Notably, an interesting finding can be seen from Figure 8, namely, that the energy structure coefficient shows a downward trend in all quantiles. This implies that the impact of the energy structure (measured by coal's share of total energy consumption) on CO_2 emissions is gradually weakening. The reason for this may be that, in recent decades, the central government of China implemented a series of policies, such as applying structural reforms to the supply side of the energy sector and prioritizing the development of renewable energy industries. As a result, the proportion of traditional fossil energy gradually declined, thus weakening the positive role of the energy structure on CO_2 emissions.

5.3. Panel Causality Analysis

To enable more precise and targeted energy policies to be drawn up, we further conducted causal relationship checks for all variables based on the D-H panel causality test, which was proposed by Dumitrescu and Hurlin [76]. Table 9 shows the results. In addition,

to clearly identify the causal relationship between variables, we also plotted the causality relationship flow, as shown in Figure 9.

Table 9. Results of the D-H panel causality test.

Null Hypothesis	High-RE Region	Low-RE Region	High-Emission Region	Low-Emission Region	Full Panel
$lnCO_2 \Longrightarrow lnRE$	2.9107 **	**0.1270**	2.0124 **	**0.2229**	2.0829 **
$lnCO_2 \Longrightarrow lnPgdp$	6.1083 ***	3.7953 ***	2.9116 ***	4.5193 ***	2.7809 ***
$lnCO_2 \Longrightarrow lnENS$	6.1812 ***	7.2909 ***	6.9740 ***	7.9234 ***	8.4656 ***
$lnCO_2 \Longrightarrow lnUrb$	**0.4335**	5.3971 ***	5.6496 ***	**1.5581**	5.2785 ***
$lnCO_2 \Longrightarrow lnTra$	2.0406 **	1.6888 *	4.0267 ***	**0.6234**	3.4415 ***
$lnRE \Longrightarrow lnCO_2$	6.8348 ***	4.1580 ***	7.2673 ***	4.1341 ***	8.1920 ***
$lnRE \Longrightarrow lnPgdp$	12.6820 ***	7.9743 ***	11.5729 ***	6.0417 ***	12.6889 ***
$lnRE \Longrightarrow lnENS$	8.7596 ***	3.2904 ***	3.6172 ***	9.8422 ***	9.2018 ***
$lnRE \Longrightarrow lnUrb$	13.4453 ***	5.0089 ***	12.7378 ***	4.1964 ***	12.3511 ***
$lnRE \Longrightarrow lnTra$	13.3164 ***	5.5044 ***	16.2709 ***	2.6374 ***	13.9845 ***
$lnENS \Longrightarrow lnCO_2$	3.1805 ***	2.6810 ***	5.6215 ***	3.2625 ***	4.4045 ***
$lnENS \Longrightarrow lnRE$	5.7292 ***	4.4023 ***	5.9382 ***	**0.3936**	4.2568 ***
$lnENS \Longrightarrow lnPgdp$	4.4640 ***	**0.9366**	2.9863 ***	2.4564 **	3.2693 **
$lnENS \Longrightarrow lnUrb$	2.5844 ***	4.7457 ***	3.6127 ***	3.6407 ***	2.8578 ***
$lnENS \Longrightarrow lnTra$	5.4698 ***	**0.4124**	4.9429 **	**1.0796**	2.0021 **
$lnPgdp \Longrightarrow lnCO_2$	15.4203 ***	7.7656 ***	12.9959 ***	8.0352 ***	15.0723 ***
$lnPgdp \Longrightarrow lnRE$	14.1972 ***	13.5024 ***	5.4679 ***	19.4541 ***	16.9224 ***
$lnPgdp \Longrightarrow lnENS$	**0.1276**	7.4647 ***	**0.7568**	5.2976 ***	3.2119 ***
$lnPgdp \Longrightarrow lnUrb$	11.6523 ***	8.7414 ***	8.8450 ***	6.9433 ***	11.2289 ***
$lnPgdp \Longrightarrow lnTra$	4.4646 ***	2.8363 ***	6.1700 ***	2.2988 **	6.1578 ***
$lnUrb \Longrightarrow lnCO_2$	2.1959 ***	2.2606 ***	2.2588 **	2.1676 ***	1.9816 **
$lnUrb \Longrightarrow lnRE$	2.7156 ***	5.1254 ***	2.6830 ***	5.3219 ***	5.5230 ***
$lnUrb \Longrightarrow lnPgdp$	4.5637 ***	6.0518 ***	5.7973 ***	5.0844 ***	7.7110 ***
$lnUrb \Longrightarrow lnENS$	2.5722 ***	4.0354 ***	3.0429 ***	2.3809 **	3.8579 ***
$lnUrb \Longrightarrow lnTra$	3.1687 ***	4.4792 ***	3.3938 ***	3.8554 ***	5.0927 ***
$lnTra \Longrightarrow lnCO_2$	4.8353 ***	6.8901 ***	9.8784 ***	7.0257 ***	6.8802 ***
$lnTra \Longrightarrow lnRE$	7.0087 ***	**0.3475**	**0.5365**	9.9738 ***	5.2016 ***
$lnTra \Longrightarrow lnPgdp$	9.2717 ***	7.0601 ***	5.3041 ***	6.4698 ***	4.2115 ***
$lnTra \Longrightarrow lnENS$	2.7430 ***	5.8916 ***	3.3907 ***	4.7269 ***	5.7968 ***
$lnTra \Longrightarrow lnUrb$	5.5479 ***	2.7532 ***	8.7199 ***	7.3233 ***	2.4655 ***

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; The values represent Wald statistics; lnA⇒ lnB denotes lnA does not cause lnB; bold values indicate no significant relationship exists between the variables.

Specifically, for the full sample, bidirectional causality was detected between variables, including the RE and CO_2 emissions, which again supports the significant impacts of the RE on CO_2 emissions, as shown in Section 4.2.3. In addition, the bidirectional causality among all of the four control variables (i.e., *ENS*, *Pgdp*, *Urb*, *Tra*) and CO_2 emissions verified the robustness of the regression results presented in Section 5.3. Moreover, it was observed that there is heterogeneous causality link among the variables across the four regions. In the high-RE and high-emission regions, the RE and CO_2 emissions exhibit a significant bidirectional causal relationship. Nevertheless, one-way causality from the RE to CO_2 emissions exists in the low-RE and low-emission regions. This implies full consideration should be given to the regional differences when formulating RE and emission reduction policies for each region by effectively controlling the influence channels.
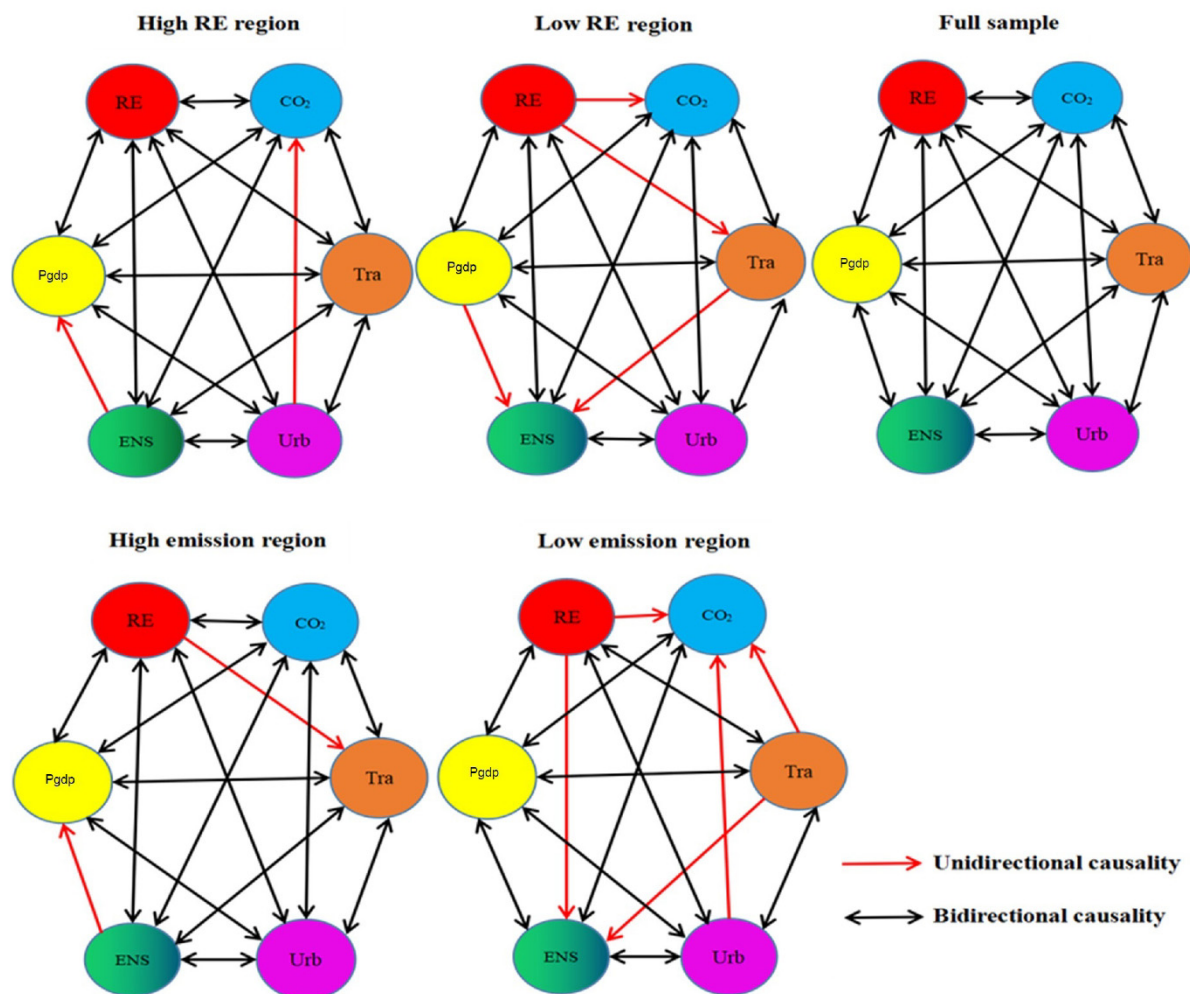
Figure 9. Causality relationship flow across different regions.

6. Conclusions

The existence of an *RE* poses a potential challenge to energy-saving and emission-reduction goals that solely rely on improvements in energy efficiency. In the context of lowering carbon emissions, attention should be paid to the RE in terms of its adverse impact on the environment. To understand the potential impacts of the RE on greenhouse gases, we attempted to evaluate the China's provincial RE values over the period 2001–2017, for the short and long run, and to explore the extent to which RE contributes to the increment in CO_2 emissions. Considering regional heterogeneity, asymmetric and regional heterogeneity analyses were further conducted. The main conclusions are as follows.

First, based on the calculation results of this study, China's national average rebound level was 90.47% in the short run, and 78.17% in the long run, during the 2001–2017 period. Most of the provinces experienced a partial RE, whereas some provinces experienced a backfire effect, such as Guangxi and Henan. Furthermore, the RE in the short run was greater than that in the long run for the whole sample. Most of the provinces having high energy rebounds were concentrated in the central and eastern regions.

Second, the empirical results indicate that an increase in the short-run RE leads to an increment in CO_2 emissions of approximately 0.818%, whereas a 1% increase in the long-run RE leads to an increment in CO_2 emissions of approximately 0.695%. Accordingly, reducing the RE can mitigate China's CO_2 emissions. With respect to the regional heterogeneity analysis, the CO_2 emissions in each of the four types of region (e.g., high-emission region, low-emission region, high-RE region, and low-RE region), particularly the high-emission and high-RE regions, are significantly and positively affected by the RE.

Third, the asymmetric analysis implies that a marginal decrease in the RE in the provinces located at higher quantiles (i.e., 50th, 75th, and 90th) promotes a greater CO_2 reduction than that in the provinces located at lower quantiles. In addition, the energy structure exerts a gradually reducing impact on CO_2 emissions across all quantiles. The D-H panel causality test indicates there is a heterogeneous causality link among the variables across the four regions. In the high-RE and high-emission regions, the RE and CO_2 emissions have a significant bidirectional causal relationship. Nevertheless, one-way causality exists from the RE to CO_2 emissions in the low-RE and low-emission regions.

Notably, this study only examined the preliminary empirical relationship between the rebound effect and CO_2 emissions, and is subject to some limitations. One limitation is associated with the specific influence mechanism in the rebound effect–CO_2 emissions relationship. Exploring how the rebound effect influences CO_2 emissions can help policymakers to accurately formulate specific strategies. Thus, in future research, we will discuss the internal direct and indirect impact mechanisms between the rebound effect and CO_2 emissions.

Abbreviations

RE	Energy rebound effect	GDP	Gross domestic product
DEPI	Dynamic comprehensive energy efficiency index	CEADs	China Emission Accounts and Database
Mtce	Million tonnes coil equivalent	CSY	China Statistical Yearbook
EKC	Environmental Kuznets curve	CESY	China Energy Statistical Yearbook
CADF	Cross-sectionally augmented Dickey–Fuller	D-GMM	Differential generalized method of moments
CD	Cross-section dependence	SYS-GMM	System generalized method of moments
Effch	Energy efficiency change	Tech	Technological progress change
k	Capital stock	L	Labor
CIPS	Cross-sectionally augmented Im, Pesaran, and Shin	CO_2	Carbon dioxide

Appendix A

Table A1. Descriptions and data sources of the variables.

Variable	Definition	Data Sources
RE	Energy rebound effect	Calculation in Section 4.1
CO_2	CO_2 emissions of each province	China Emission Accounts and Database
GDP	Gross domestic product (GDP) of each province	CSY (2018)
P	Energy price (P) was measured by the price index of fuels	CSY (2018)
E	Total energy consumption of each province	CESY (2018)
K	Capital input (K) was calculated based on the perpetual inventory method	CSY (2018)
L	Labor input (L) was measured by employee number of each province at the end of the year	CSY (2018)
DEPI	Dynamic comprehensive energy efficiency index	Calculation in Section 4.1
Pgdp	Per capita gross domestic product (GDP) of each province	CSY (2018)
ENS	Energy structure (ENS) was measured by coal consumption as a percentage of total energy consumption	CESY (2018)
Urb	Urbanization (Urb) was calculated by the ratio of permanent urban population to total population	CSY (2018)
Tra	Trade openness (Tra) was presented as the ratio of net trade imports and exports to the aggregate GDP	CSY (2018)

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