Article

The Impact of Economic Growth, Industrial Transition, and Energy Intensity on Carbon Dioxide Emissions in China

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Abstract: Carbon emission reduction has become a worldwide concern on account of global sustainability issues. Many existing studies have focused on the various socioeconomic influencing factors of carbon dioxide (CO_2) emissions and the corresponding transmission mechanisms, while very few models have unified the scale effect, structure effect, and technique effect in the context of China. This paper attempted to analyze the impact of economic growth, industrial transition, and energy intensity on CO_2 emissions in China by constructing an autoregressive distributed lag (ARDL) model. The results showed that there are long-term cointegration relationships between the three factors mentioned above and CO_2 emissions. There is an inverted U-shaped relationship between economic growth and CO_2 emissions, which not only verifies the environmental Kuznets curve (EKC) hypothesis, but also upholds the scale effect. In addition, the proportion of added value of secondary industry and energy intensity has significant positive impacts on CO_2 emissions. On one hand, this confirms the structure effect and technique effect; on the other hand, it implies that the reduction effect is the dominant effect in the case of China, instead of the rebound effect. This paper is expected to make a valuable contribution to research in the field of sustainable development by providing both theoretical support and implementation of path choice for CO_2 reduction in China.

Keywords: carbon dioxide emissions; economic growth; industrial transition; energy intensity; ARDL model

1. Introduction

As stated in the Paris Agreement, climate change is the biggest non-traditional security challenge facing the world [1,2], and it is a major sustainable development issue that needs to be solved urgently. Reducing greenhouse gas emissions to cope with climate change has become a global consensus [3], which jeopardizes three aspects of global sustainable development: economic sustainability, environmental sustainability, and social sustainability [4].

At present, more than 50 countries have reached their carbon peaks. The United States reached its carbon peak in 2007. The carbon peak time of EU member states was realized in 1990 as a group. Japan attained its carbon peak in 2013 [5]. More than 130 countries and regions have proposed "zero carbon" or "carbon neutral" climate goals. Developed countries and regions represented by the United States, the European Union, and Japan plan to achieve carbon neutrality by 2050, while the United Kingdom and Sweden have included carbon neutrality into substantive legislation [6].

As the country with the world's second largest economy, China is also a major global energy consumer and CO_2 emitter that plays an important constructive role in global climate governance [5]. On 22 September 2020, China announced that it would enhance its nationally determined contribution and adopt more effective policies and measures to reach the peak of CO_2 emissions by 2030 [7,8] and achieve carbon neutrality by 2060 [9]. Different from developed countries and regions, such as the United States and Europe, China is still

in the stage of rising CO_2 emissions and has not yet reached its carbon peak. In order to achieve sustainable development, China has been facing tremendous pressure to reduce the CO_2 emissions. Therefore, it is very important to explore the key influencing factors of CO_2 emission in China, and then to clarify the corresponding transmission mechanisms.

In the current literature on sustainable development, the influencing factors of CO_2 emissions mainly include the following: fairness of income distribution, international trade and transfer of greenhouse gas, industrial structure evolution, technological progress and energy efficiency, governmental institutional framework, environmental policy, and consumer preference [10]. The transmission mechanisms of the influencing factors for CO_2 emissions lie primarily in the following three aspects: the scale effect, structure effect, and technique effect [11]. Due to the differences in research areas and research methods, the correlation of influencing factors and their corresponding transmission mechanisms are not consistent.

There are many studies that are designed to explore the influencing factors of CO_2 emissions from one single perspective of either the scale effect, structure effect, or technique effect, but there are very few to unify the scale effect, structure effect, and technique effect within the same research framework, and to clarify the transmission mechanisms of influencing factors on CO_2 emissions. This paper intends to contribute to this important research area by providing theoretical support and the implementation of path choice for CO_2 reduction in China. The rest of this article is arranged as follows: Section 2 reviews the current literature, Section 3 provides data and research methods, Section 4 displays empirical results, and Section 5 discusses the results and summarizes the paper.

2. Literature Review and Related Hypotheses

2.1. Literature Review

With global warming and climate change, it is crucial to have a clear understanding of the drivers of CO_2 emissions [12] to formulate policies for the goal of CO_2 emission reduction [13].

Studies on the relationship between economic growth and CO_2 emissions have been presented in a lot of the literature [14–17], with most studies focusing on the theoretical framework of Environmental Kuznets Curve [18]. In 1991, for the purpose of cognizing the possible impact of the North American Free Trade Agreement on the environment, Grossman and Krueger used a simplified regression model to conduct an empirical analysis on per capita GDP and environmental degradation for the first time. They found that the relationship between per capita GDP and environmental degradation presented in an inverted U-shaped curve [19]. Built on this groundbreaking work, Grossman and Krueger discovered that among the most considered environmental degradation indicators, economic growth leads to environmental degradation in the initial stage, and environmental quality is improved with further growth of the economy [20]. These conclusions have been confirmed by other studies. For example, with the cross-country panel data, Panayotou investigated the relationship between environmental degradation and per capita GDP. His result showed an inverted-U shaped curve, namely an EKC relationship [21].

The first batch of EKC empirical studies appeared in the early 1990s [22], and the main data source of pollutants and CO_2 came from the Global Environmental Monitoring System, the Oak Ridge National Laboratory, and OECD Environmental Data Program [11].

Many economists believe that GDP (or income) has significant impact on most environmental quality indicators [20,23]. In the early stage of economic development, most of environmental indicators deteriorate with GDP growth; as countries become richer, environmental degradation can be ameliorated. Empirical research also suggests that countries are likely to "get out" of environmental degradation eventually, although this process will not happen spontaneously. These studies lay a theoretical and empirical foundation for further research on EKC, and the main challenge of subsequent research will be to find influencing factors other than GDP that lead to the EKC type relationship.

2.1.1. Scale Effect, Structure Effect, and Technique Effect

Many scholars agree that structural change and technological progress are the main factors leading to different EKC modes [24]. Structural change includes the shift of production from high-emission industries to information technology-based services (which are called low-emission industries); technological progress includes technological improvement that leads to the reduction of the factor effect in the production process, or the use of production technology that is beneficial to the reduction of pollution output [25].

As it is shown in Figure 1, during the primary (or agricultural) production stage, the consumption of natural resources and the expansion of production scale cause environmental degradation (which is called the scale effect of production on environmental degradation), and EKC is on the rise. With the transformation of production from agriculture to industrialization, economic growth leads to the development of high-tech industry and tertiary industry, accompanied by the improvement of production technology and clean energy technology, which are called the structure effect and technique effect, respectively. Both of these effects can overcome the scale effect, and make EKC into a downward trend [26].
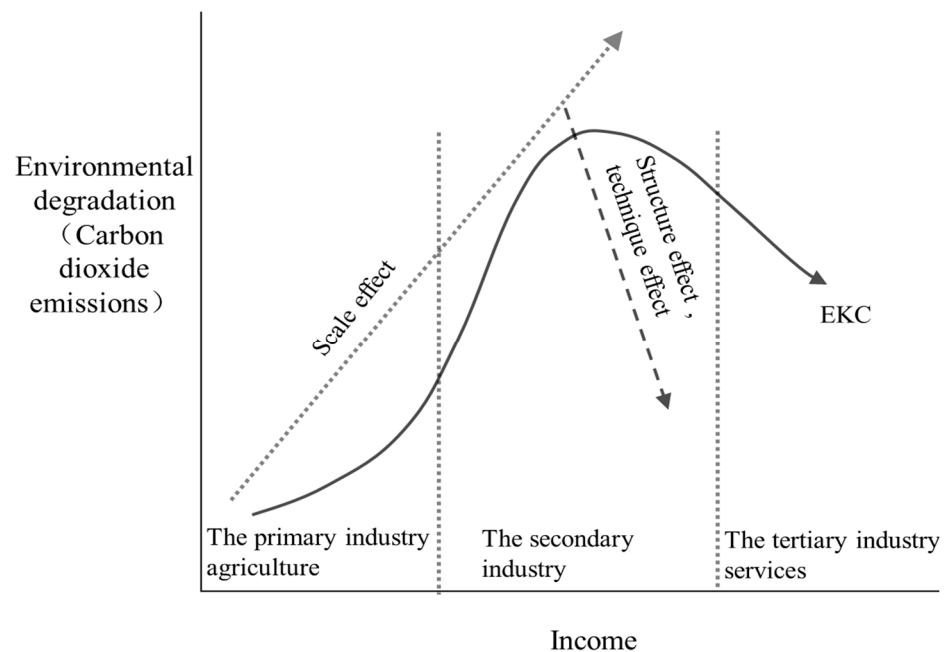
Figure 1. The effect of scale, structure, and technique on CO_2.

The structure effect is caused by the transformation of the production mode from high-energy-input industries to environmentally friendly industries. The initial CO_2 increase is due to a shift in the industrial structure from light industry to heavy industry, but the subsequent shift to low-emission information-based industries and services would drive CO_2 emissions down [25].

The technique effect is the result of technological progress. On one hand, technological progress improves the efficiency of factor allocation and drives the factor input of per unit output to decrease. On the other hand, the investment in environmental research and development promotes the development of clean technology, which makes it possible to replace "dirty" or outdated technologies with cleaner technologies. The investment in environmental research also needs to be supported by a certain level of economic development [27].

Technological progress is the main reason for improving environmental quality [13]. By selecting the instrumental variables of structural change and technological progress, Bruyn et al. [28] concluded that the decline in emissions is due to technological progress and structural change, rather than to economic growth. Considering suspended particulate

matter (SPM), the variation in pollution level in spatio-temporal dimensions is attributed to the progress of production technology and the evolution of industrial structure [24]. Taking Ecuador as an example, improving the level of fossil fuel technology and optimizing the industrial structure make it possible to control CO_2 emissions with the continuous growth of GDP [29]. Studies on Malaysia and OECD members have also reached similar conclusions [30].

However, structural change and technological progress may only have short-term effects on environment [22]. Grossman and Krueger [20] pointed out that the improvement of the environment not only comes from technological innovation, but it also reflects specific external conditions, such as politics, the economy, and technology, within the research time range. EKC may reflect the cycle of internal and external effects caused by technological innovation in the short term. In the long term, nonlinear EKC is a set of economic-environmental relationships corresponding to different technologies [11]. Different countries have heterogeneous characteristics, and there is no definitive evidence that China may follow the evolutionary trajectory of other countries' EKC.

2.1.2. Energy Intensity

Energy is the core of environmental problems, so energy should also be the core of solutions to environmental problems. The key to improve environmental degradation lies in the reduction of energy intensity (which refers to energy consumption per unit GDP) [7,31]. In order to mitigate energy intensity, many policy frameworks have emerged. For example, the EU's "2050 Energy Route" aims to achieve its reduction target through the implementation of energy efficiency policies, with the intention of mitigating climate change [31]. According to the literature, the impact of energy intensity on CO_2 emissions mainly has the following two divergent mechanisms: many studies argue that energy intensity has a reduction effect on CO_2, while some scholars support a rebound effect.

The decoupling assessment between economic growth and energy consumption is a core issue in the field of sustainable development [32]. Many studies emphasize the importance of the reduction of energy intensity, the optimization of energy structure, and the improvement of conversion efficiency. The reduction effect can be understood as the following: by reducing energy consumption per unit of GDP, the amount of energy consumption may be lower, hence, CO_2 emissions will be lessened [33]. Due to the oil crisis of the 1970s, energy intensity has become a critical issue. Oil-based economic structures must be transformed with new technologies to reduce energy consumption per unit of output, and to strengthen the development of low-polluting services [33].

Most EKC empirical studies state that both CO_2 emissions and energy consumption are highly relevant to economic growth. In the long run, industrial growth will affect energy consumption, and then CO_2 emissions [5]. The main reason is that economic growth is always accompanied by energy consumption, which is mainly based on fossil fuels that produce CO_2 emissions [6,7]. Based on the boundary test method of the ARDL model, Begum et al. [34] tested the dynamic impact of GDP, energy consumption, and population growth on CO_2 emissions in Malaysia. Their results confirmed that per capita energy consumption and per capita GDP have long-term positive impacts on per capita CO_2 emissions. Empirical studies on India also show that energy consumption is the Granger cause of CO_2 emissions and economic growth [35], and similar conclusions have been confirmed in EU member states [36] and sub-Saharan African countries [37].

The evolution of energy intensity depends on a variety of factors, such as energy price and energy structure [12], and many EKC studies focus on this field. Stern [38] believes that the main reason for the decline in energy intensity over time is the shift from the direct use of fossil fuels to higher quality fuels, especially electricity. Fuel structure change is closely related to technological innovation [38,39]. Moreover, energy intensity changes are not uniform in all countries [5,6].

Technological advances can improve energy efficiency, and thereby reduce energy use, which leads to less frequent use of natural resources to produce energy. This consequently

improves environmental degradation. It is important to mention that, although over time energy intensity is decreasing, which implies that energy efficiency is increasing [38], many studies have shown that increased energy efficiency may lead to increased energy consumption, which may ultimately lead to increased environmental degradation or increased CO_2 emissions [40]. This phenomenon, known as the rebound effect of energy intensity on CO_2 emissions, is essential to understanding sustainable development.

Empirical estimations of the rebound effect tend to focus on producer behavior and consumer behavior at the same time [40]. Due to different assumptions, relevant data, and the negotiation power of both parties in the market, the estimated results are quite different [41]. The logic of these studies is that increased energy efficiency leads to lower energy prices, which may lead to increased energy consumption [40]. Thus, in the long run, CO_2 reductions resulting from technological advances may be offset by increases in energy consumption [42]. The research framework of sustainable development should not understate the aforementioned scenario.

2.2. Research Hypotheses

To sum up, in the context of China's sustainable development, it is meaningful to explore the scale effect, structure effect, and technique effect on CO_2 emissions. Within a research framework, it is essential to probe whether the reduction effect or the rebound effect is the dominant effect overall. Therefore, this paper intends to carry out some explorations in this respect, in order to make a marginal contribution to research in the field of sustainable development.

Hypothesis 1 (H1). *There are long-term cointegration relationships between China's economic growth, industrial transition, energy intensity, and CO_2 emissions.*

As reviewed in Section 2.1, based on the EKC hypothesis, this paper is designed to integrate the scale effect, the structure effect, and the technique effect into one research framework. The effects of scale, structure and technique are represented by economic growth, industrial transition, and energy intensity, respectively. It is assumed that there are long-term cointegration relationships between them and CO_2 emissions. The alternative hypothesis is that there are no long-term co-integration relationships between China's economic growth, industrial transition, energy intensity, and CO_2 emissions.

Hypothesis 2 (H2). *China's energy intensity has significant reduction effect on CO_2 emissions.*

As mentioned in Section 2.1, the role of energy intensity in carbon dioxide emissions is debatable. The existing literature shows that there is a positive or negative correlation between energy intensity and carbon dioxide emissions. Due to the different strengths of reduction effect and rebound effect, it is impossible to judge the impact direction of China's energy intensity on carbon dioxide emissions. Therefore, this paper intuitively assumes that China's energy intensity has a significant reduction effect on carbon dioxide emissions. The alternative assumption of Hypothesis 2 is that China's energy intensity has no significant reduction effect on CO_2 emissions.

3. Data and Method
3.1. Data

According to the process of econometric analysis, the annual time-series data were applied from 1980 to 2019. The variables' descriptions and implications are shown in Table 1. Specifically, the total amount of CO_2 emissions in China is calculated by multiplying the CO_2 emission factors of various fossil energy sources and their consumption [43,44], and is taken as the dependent variable.

Table 1. Variable description.

Variable Name	Code	Unit	Implication
CO$_2$ emissions	CARBON	Ton	Environmental degradation
GDP	GDP	1980 constant price yuan	Economic growth, scale effect
Proportion of the added value of the secondary industry	INDUSTRY	%	Industrial transition, structure effect
Energy intensity	ENERGY	Kilograms of standard coal per unit added value	Technique effect

Motivated by the EKC hypothesis, which serves as the benchmark regression framework, the following variables were included: Economic growth (*GDP*) and its quadratic term, industry transition (*INDUSTRY*), and energy intensity (*ENERGY*). To be specific:

1. Economic growth (*GDP*) and its quadratic term. GDP was treated as the proxy variable of economic growth and the scale effect to eliminate the influence of price factors, and GDP was converted to the constant price in 1980. These terms were included in the independent variables to examine the EKC hypothesis [19,43,45].
2. Industry transition (*INDUSTRY*). The proportion of added value of secondary industry in GDP calculated at current prices was not only chosen for the proxy variable of the industrial transition, but also taken as the proxy variable of the structure effect.
3. Energy intensity (*ENERGY*). Since energy intensity is a measure of energy efficiency [46–48], which can reflect the level of technology, this paper selects energy intensity as the proxy variable of technique effect. Furthermore, whether energy intensity has a significant reduction effect or rebound effect on CO$_2$ emissions was explored.

3.2. Model Estimation

Based on the study of the EKC hypothesis, referring to the idea of the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model [43,46], an empirical model was established with environmental degradation (*ED*) as the dependent variable and the scale effect (*SCALE*), structure effect (*STRU*), and technique effect (*TECH*) as the independent variables:

$$ED_t = aSCALE_t^b STRU_t^c TECH_t^d e_t \qquad (1)$$

where *t* represents time (1980, 1981, . . . , 2019); *a* is a constant term; *b*, *c* and *d* represent coefficients determining the effects of scale effect, structure effect, and technique effect, respectively; and e_t represents the error term.

The coefficients *a*, *b*, *c*, and *d* can be estimated by ordinary least squares (OLS) in a linear form by taking logarithms to Equation (1), that is:

$$lnED_t = lna + blnSCALE_t + clnSTRU_t + dlnTECH_t + e_t \qquad (2)$$

Equation (2) is the benchmark regression established in our analysis. It can be seen as a framework indicating three dimensions contributing to environment degradation. Motivated by [44–46], including the variables shown in Table 1, Equation (2) can be extended into Equation (3).

$$lnCARBON_t = \alpha_0 + \alpha_1 lnGDP_t + \alpha_2 (lnGDP_t)^2 \\ + \alpha_3 lnINDUSTRY_t + \alpha_4 lnENERGY_t + \varepsilon_t \qquad (3)$$

In Equation (3), α_0 is the constant and ε_t represents the error term; the subscript *t* indicates the year (1980, 1981, . . . , 2019). The econometric model above is not linear [47]. In order to obtain consistent and useful results, all variables were converted into natural logarithms [48].

3.3. Econometric Methodology

Several methods were adopted in the econometric analysis; (i) Fisher-ADF and PP-Fisher unit root tests were used to check the stationarity of all variables, and (ii) Bounds test and ARDL model were constructed to investigate the presence of short-run and long-run relationships among the series. It should be noted that existing studies suggest the bounds test is a desirable cointegration method [49,50], because it is applicable regardless of whether the variables are stationary, first-order differential stationary, or a mix of both. It also works well for endogenous bias [51]. Meanwhile, it is more robust and suitable for small samples than the Engle Granger two-step method and Johansen cointegration test [52].

The form of ARDL model established in this paper is as follows:

$$
\Delta lnCARBON_t = \alpha_0 + \sum_{i=1}^{m_1} \varphi_1 \Delta lnCARBON_{t-i} + \sum_{i=0}^{m_2} \varphi_2 \Delta lnGDP_{t-i} +
$$
$$
\sum_{i=0}^{m_3} \varphi_3 \Delta (lnGDP_{t-i})^2 + \sum_{i=0}^{m_4} \varphi_4 \Delta lnINDUSTRY_{t-i} + \sum_{i=0}^{m_5} \varphi_5 \Delta lnENERGY_{t-i} +
$$
$$
\beta_1 lnGDP_{t-1} + \beta_2 (lnGDP_{t-1})^2 + \beta_3 lnINDUSTRY_{t-1} + \beta_4 lnENERGY_{t-1} + \varepsilon_t
$$
(4)

In Equation (4), $lnCARBON$ is the dependent variable; Δ is the difference operator; $\beta_1, \beta_2, \beta_3, \beta_4$ represent the long-run coefficients; $m_i (i = 1, 2, 3, 4, 5)$ is the lag length; α_0 indicates the constant; and ε_t shows the error correction term (the residual term is assumed to be homo-variance and there is no sequence correlation [53]). The null hypothesis of the bounds test assumes that there is no long-term cointegration relationship between the variables (namely $H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$), while the alternative hypothesis assumes the existence of a long-term cointegration relationship (namely $H_1 : \beta_1 \neq, \beta_2 \neq, \beta_3 \neq, \beta_4 \neq 0$).

4. Results

4.1. Unit Root Test

As far as modeling time-series data is concerned, it is necessary to investigate the stationarity of time-series data firstly. Additionally, the bounds test cannot be used when the variables are second order and above difference stationary [51]. In this paper, the Fisher-ADF unit root test and PP-Fisher unit root test were carried out on the involved time-series data. The null hypothesis is that there is unit root; that is, the time-series data are not stable. The results are shown in Table 2, suggesting that all variables selected in this paper are stationary in the level or the first difference.

Table 2. Unit root test.

Variables	Augmented Dicey-Fuller	Phillips-Perron
	(ADF)	(PP)
Level	Test-Statistic Value	
$lnCARBON_t$	2.2704	4.2438
$lnGDP_t$	−1.7452	−1.7367
$(lnGDP)^2{}_t$	−0.2391	−2.3307
$lnINDUSTRY_t$	−0.7178	−1.1312
$lnENERGY_t$	−2.8692 ***	−5.0581 ***
First Difference	Test-Statistic Value	
$\Delta lnCARBON_t$	−3.1115 **	−3.2551 **
$\Delta lnGDP_t$	−3.8251 ***	−3.3237 **
$\Delta (lnGDP)^2{}_t$	−3.9623 ***	−3.4891 **
$\Delta lnINDUSTRY_t$	−3.9028 ***	−3.8744 ***
$\Delta lnENERGY_t$	−1.9751 **	−1.7283 *

*, **, *** indicate rejection of the null hypothesis at the 10%, 5%, 1% significance level, respectively.

4.2. Bounds Test

When performing the bounds test, it is essential to select an optimal lag length. Different lag length criteria, such as Akaike information criterion (AIC), Hannan Quinn (HQ) information, and Schwarz Bayesian criterion (SBC) can be used to determine the optimal lag length. In this paper, based on the principle of minimum error, the lag order of the model was selected by the AIC criterion in order to obtain more consistent results [54]. Then the bounds test was utilized to assess the long-term cointegration relationship of the variables. The results of bounds test are presented in Table 3. It is clear that the F-statistic (4.968918) is above the upper bound critical value at 1% significance level (4.37), which indicates a long-term cointegration relationship among the variables.

Table 3. Bounds test results.

Test Statistics	Value	
F-statistic	4.968918	
Critical Value Bounds		
Significance	Lower Bound	Upper Bound
10%	2.20	3.09
5%	2.56	3.49
2.50%	2.88	3.87
1%	3.29	4.37

4.3. Econometric Model Results

As mentioned above, both the short-term and long-term ARDL models are designed, and the Ramsey RESET test is used to verify whether the model is set correctly. The null hypothesis of the Ramsey RESET test is that the model is set correctly, and the test results show that the *p*-value of the test statistic is 0.2917 (greater than 0.05). Therefore, at the significance level of 5%, the null hypothesis cannot be rejected and the model presented in this paper can be considered correct. The results of the ARDL model are shown in Tables 4 and 5, respectively.

Table 4. ARDL short-run results.

Variable	Coefficient	*t*-Statistics
$\Delta lnCARBON_{t-1}$	0.18	1.5431
$\Delta lnCARBON_{t-2}$	0.25 **	2.6302
$\Delta lnGDP_t$	10.34 ***	4.5566
$\Delta lnGDP_{t-1}$	5.72 **	2.3315
$\Delta(lnGDP)^2{}_t$	−0.49 ***	−4.1719
$\Delta(lnGDP)^2{}_{t-1}$	−0.34 **	−2.5862
$\Delta lnINDUSTRY_t$	0.46 ***	3.0803
$\Delta lnENERGY_t$	1.23 ***	6.8269
$\Delta lnENERGY_{t-1}$	−0.18	−0.6518
$\Delta lnENERGY_{t-2}$	−0.70 ***	−3.8473
ECM_{t-1}	−0.60 ***	−6.3749

** and *** indicate rejection of the null hypothesis at the 5% and 1% significance level, respectively.

Table 5. ARDL long-run results.

Variable	Coefficient	*t*-Statistics
$lnGDP$	2.56 ***	5.4005
$(lnGDP)^2$	−0.05 **	−2.8085
$lnINDUSTRY$	0.60 **	2.2700
$lnENERGY$	1.77 ***	9.4489
$Constant$	−13.13 ***	−3.8448

** and *** indicate rejection of the null hypothesis at the 5% and 1% significance level, respectively.

4.3.1. ARDL Short-Run Results

The short-term estimation results of the ARDL model are shown in Table 4. The results show that the short-term elasticity coefficients of GDP are significantly positive, and the short-term elasticity coefficients of GDP square term are significantly negative, which verifies the existence of an EKC relationship. The short-term elasticity coefficient of energy intensity in the current period is positive and significant at the 1% significance level, while the short-term elasticity coefficient of two-lag phase is negative and significant at the 1% significance level. In other words, the impact of energy intensity on CO_2 emissions in the short term is uncertain. More importantly, the coefficient of the error correction term (ECT_{t-1}) is about −0.6, and it is significant at 1% significance level. This indicates that the short-term disequilibrium will be corrected and converge back towards long-term equilibrium.

4.3.2. ARDL Long-Run Results

As presented in Table 5, the long-term elasticity coefficients of GDP and its square term are about 2.56 and −0.05, respectively, which are significant at the significance level of 5%. There is an inverted U-shaped relationship between GDP and CO_2 emissions, which indicates that there is an EKC relationship. Energy intensity has positive effect on CO_2 emissions. The long-term elasticity coefficient is 1.77, which is significant at the 1% significance level. This means that when holding other variables constant, a 1% increase in energy intensity will increase CO_2 emissions by about 1.77% on average. The development of the secondary industry has a positive effect on CO_2 emissions, and its long-term elasticity coefficient is about 0.60, which is significant at the 5% significance level. That is, while controlling other factors, for every 1% increase in the value-added share of the secondary industry, CO_2 emissions will be increased by about 0.60% on average.

4.3.3. Residual Diagnostics

In order to test whether the model has serial correlation and heteroscedasticity, the Breusch-Godfrey LM test and Breusch-Pagan-Godfrey (B-P-G) test [55] were carried out separately. The test results are shown in Table 6. The null hypothesis (H_0) for LM test is that there is no serial correlation. If the *p*-value is higher than 0.05, then the H_0 of LM test cannot be objected at the significance level of 5%; that is, there is no significant evidence for the presence of a serial correlation. The null hypothesis of B-P-G test is that there is no heteroscedasticity. Similar to the LM test, if the *p*-value of the test statistic is higher than 0.05, the null hypothesis cannot be rejected at the significance level of 5%. As shown in Table 6, *p*-values of both tests are higher than 0.05, which means that the residual term of the ARDL model constructed above has no sequence correlation and no heteroscedasticity.

Table 6. Diagnostic analysis results.

|	Breusch-Godfrey LM Test	Breusch-Pagan-Godfrey Test
F-statistic	0.3355	1.6343
(*p*-value)	(0.7189)	(0.1466)
χ^2-statistic	1.2011	18.8629
(*p*-value)	(0.5485)	(0.1703)

χ^2-statistic represents the Chi-squared statistic which is calculated by multiplying the number of observations by R-squared

4.3.4. Model Stability Diagnosis

In addition, the cumulative sum (CUSUM) test and the cumulative sum square (CUSUMSQ) test [56] were used for stability diagnosis. As shown by Figures 2 and 3, both the CUSUM line and the CUSUMSQ line do not exceed the error limit under the significance level of 5%; therefore, the parameters used in the study are stable.
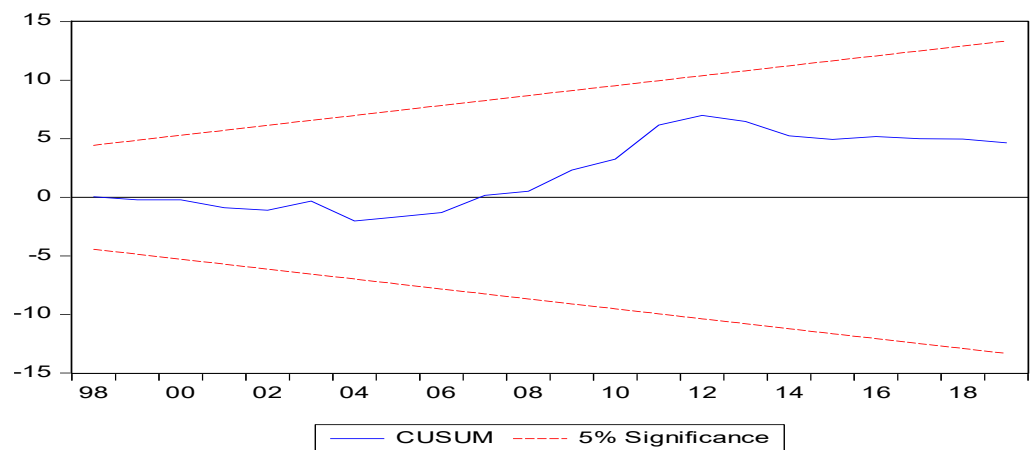
Figure 2. Cumulative Sum of Recursive Residuals.
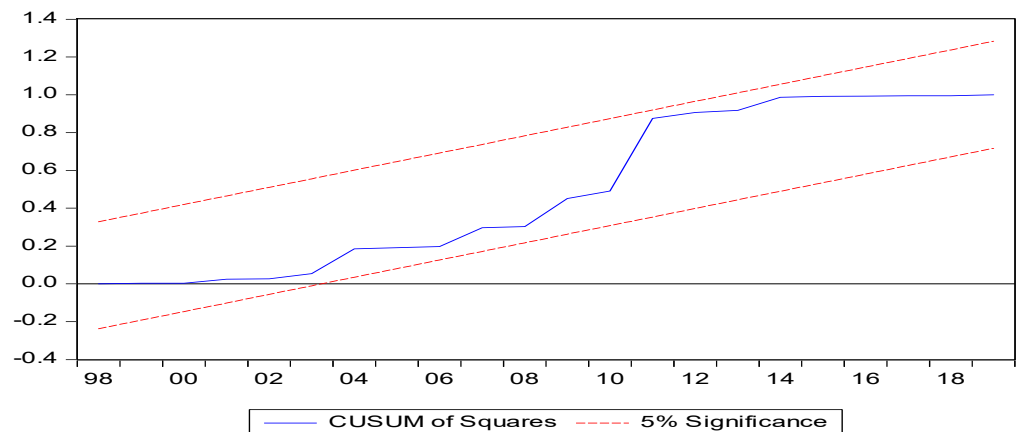
Figure 3. Cumulative Sum of Squares of Recursive Residuals.

5. Conclusions and Policy Implications

This paper empirically investigated the impact of economic growth, industry transition, and energy intensity on CO_2 emissions within the Environmental Kuznets Curve theoretical framework, in the context of China' sustainable development. The scale effect, structure effect, and technique effect on CO_2 emissions were designed within a research framework, and this paper investigated whether the reduction effect or the rebound effect is the dominant effect overall. The bounds test and the ARDL model were constructed in the study with the annual time-series data from 1980 to 2019 in China. Furthermore, a CUSUM test and a CUSUMSQ test were adopted to check the stability of the empirical model. After a series of statistical tests, it can be shown that the model established in this paper is considered to be effective and meaningful.

The results of the ARDL model show that the long-term and short-term elasticity coefficients of GDP are significantly positive, while the long-term and short-term elasticity coefficients of its square term are significantly negative, which verifies the inverted U-shaped relationship between economic growth and CO_2 emissions. This confirms that there is a scale effect of economic growth on CO_2 emissions (in other words, economic growth leads to the increasing CO_2 emissions) in the initial stage, and implies that economic growth contributes to the reduction of CO_2 emissions after passing the turning point of EKC. This provides theoretical support for China's CO_2 emissions reduction; it is too poor to be low carbon. That is, promoting the level of economic development to surpass the threshold is a crucial way to mitigate CO_2 emissions.

Regarding the proportion of added value of secondary industry in GDP, its short-term and the long-term elasticity coefficients are positive. This means that the development of secondary industry contributes to the increase in CO_2 emissions in the short and long run;

hence, the existence of the structure effect on CO_2 emissions is confirmed. It suggests that driving the transformation of secondary industry to service industry is an effective measure to achieve of target of CO_2 emissions reduction. Meanwhile, according to the National Bureau of Statistics of China, as it is shown in Figure 4, the proportion of added value of tertiary industry has been well improved and will continue to develop, which implies that special attention should be paid to the low-carbon process of industry transition.
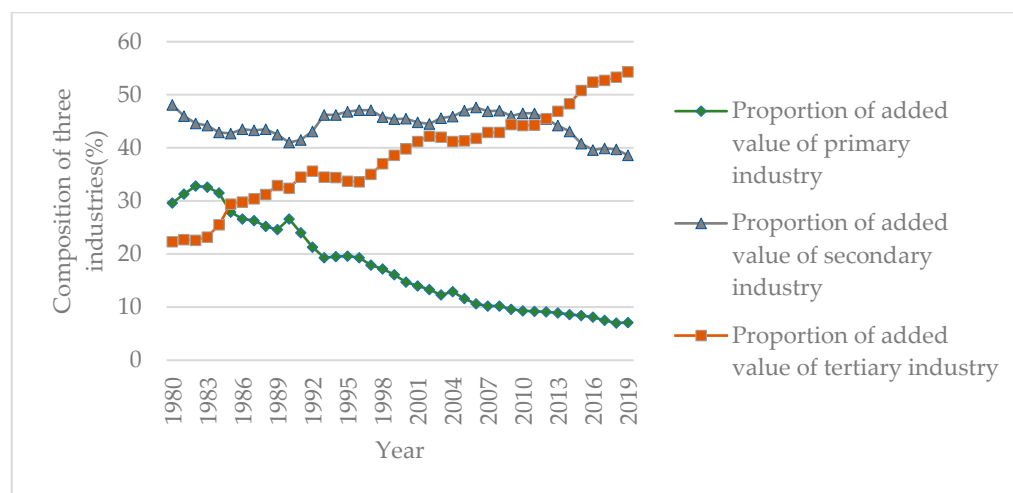
Figure 4. Trends in the composition of three industries of China from 1980 to 2019.

As far as energy intensity is concerned, the directions of its short-term elasticity coefficients are uncertain, but the long-term elasticity coefficient is positive. This argues the existence of the technique effect on CO_2 emissions and verifies that the reduction effect is the dominant effect in the case of China, instead of the rebound effect. In other words, driving energy intensity down to improve energy efficiency is an alternative path for China to achieve a CO_2 reduction.

Based on this work, future research can be divided into three directions: (1) It is worth studying how to more reasonably and precisely select the proxy instrument variables of scale effect, structure effect, and technique effect of CO_2 emissions; (2) While defining China's regional industry transition model, the construction a panel data model is expected, in order to explore the transmission mechanism of industry transition on CO_2 emissions; (3) In order to ensure the robustness of the research results, future studies can be based on other valid CO_2 emission databases.

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