Asymmetric Influence of Economic Growth on the CO\textsubscript{2} Emissions from Construction Industry in China

Jianbao Chen and Fen Li*
College of Mathematics and Informatics, Fujian Normal University, Fuzhou, China

*Corresponding author email: lifen18459191151@126.com

Abstract. In order to analyse the asymmetric impact of economic development on the carbon emissions from construction industry in China, this paper constructed an extended model of influencing factors for CO\textsubscript{2} emissions from construction industry including economic growth, collected the relevant data of China’s 30 provinces during 1997-2015, and tested threshold effect of China's economic growth on CO\textsubscript{2} emissions from construction industry by the panel threshold regression model empirically. The results show that: (1) Economic growth, population size, industrial scale and energy structure have positive impacts on CO\textsubscript{2} emissions from construction industry, while energy efficiency has negative impacts. (2) Economic growth has a significant double threshold effect on CO\textsubscript{2} emissions of construction industry, and it has a positive effect under the three regimes. Its intensity of effect increases first and then decreases with the economic level across the two thresholds. As a result, the Chinese government should pay more attention to the asymmetric influence of economic growth at different stages of development when formulating the construction industry emission reduction policies.

1. Introduction
Under the background of increasing global greenhouse effect, how to reduce CO\textsubscript{2} emissions and achieve the sustainable development of economic and social has become a hot topic of concern. According to statistics, China's current CO\textsubscript{2} emissions rank first in the world. The “13th Five-Year Plan for Energy Conservation and Emission Reduction Comprehensive Work Plan” issued by the State Council of China in 2016 proposed that carbon emission reduction tasks should be implemented at various industry levels. The construction industry is characterized by high energy consumption, high emissions, and low energy efficiency, and has great potential for carbon emission reduction. Therefore, it is worth studying and exploring the relationship between China's economic growth and CO\textsubscript{2} emissions in the construction industry, and looking for a low-carbon development path for the Chinese construction industry.

As people pay more attention to global warming, the CO\textsubscript{2} emission of the construction industry has also attracted widespread attention in academia. The existing relevant literature mainly focuses on calculating CO\textsubscript{2} emissions\cite{1-3} and investigating the linear effects of main influencing factors on it\cite{4-7}. Most of the research methods are based on linear regression model, and most of the sample selection is time series or cross-section data. Therefore, based on the relevant data of 30 provinces in China during 1997-2015, this paper attempts to use the panel threshold regression model to explore whether there is a significant threshold effect in the process of China's economic growth on the carbon emissions from the construction industry, and find out several possible thresholds. Compared with the ordinary linear regression model, the panel threshold regression model can study the heterogeneity effect of a certain influencing factor in different threshold range, and the conclusion of the nonlinear
model is more objective and more in line with the actual situation. By revealing the asymmetric influence of China’s economic growth on the carbon emission from construction industry, it is helpful to find out the new law of reducing the carbon emission from construction industry and provide valuable reference for the coordinated development of China’s economy and construction industry in low carbon and environmental protection.

2. Model and Methodology Specification

2.1. Theoretical Model Derivation

The \textit{IPAT} identity proposed by Ehrlich and Holdren[8] is used to investigating the impact of economic activity on the degree of environmental pollution:

\begin{equation}
I = P \cdot A \cdot T
\end{equation}

where \(I\) represents the emission level of a pollutant, \(P\) is the population size, \(A\) indicates the economic level of a society and \(T\) is the technology index.

We found that the \textit{IPAT} model is too simple and has some limitations, it assumes that the elasticity coefficients of \(P\), \(A\) and \(T\) to \(I\) are consistent, which conflicts with the \textit{EKC} hypothesis. Therefore, based on the \textit{IPAT} model, Dietz and Rosa[9] proposed the \textit{STIRPAT} model to examine the influencing factors of environmental change better:

\begin{equation}
I_t = aP_t^b A_t^c T_t^d \xi_t
\end{equation}

where \(I\), \(P\), \(A\) and \(T\) are the same as in equation (1); \(a\) denotes the intercept term; \(b\), \(c\) and \(d\) are coefficients corresponding to \(P\), \(A\) and \(T\) respectively, \(\xi_t\) is the random error term; subscript \(t\) indicates the time. In order to facilitate hypothesis testing and eliminate the heteroskedasticity possibly existing in the model, all variables take logarithmic form[10]. Since the sample data is the panel data, so we add the subscript \(i\) in the model to express provinces. Thus equation (2) can be written as follows:

\begin{equation}
\ln I_{it} = \ln a + b (\ln P_{it}) + c (\ln A_{it}) + d (\ln T_{it}) + \epsilon_{it}
\end{equation}

Considering the actual situation of China’s construction industry, we expand equation (3) to obtain the extended model of influencing factors for CO2 emissions from construction industry:

\begin{equation}
\ln CO_{2it} = \ln a + \beta_1 \ln POP_{it} + \beta_2 \ln PGDP_{it} + \beta_3 \ln ENE_{it} + \beta_4 \ln ENS_{it} + \beta_5 \ln IS_{it} + \epsilon_{it}
\end{equation}

where the \(CO_2\) is total CO2 emissions of the construction industry (10^4 tons); \(POP\) denotes population size of each province (10^4 people); \(PGDP\) represents economic level and is measured in real per capita GDP of 1997 constant yuan; \(ENE\) is energy efficiency, proxied by actual total outputs in the construction industry divided by its total energy consumption, which reflects technical advancement of the construction industry (10^4 yuan per tce); \(ENS\) is the proportion of coal consumption in the construction industry to its total energy consumption, that is, energy structure (%); \(IS\) indicates the industry scale of the construction sector (added value of construction industry/GDP-%); \(a\) is the intercept and \(e\) is disturbance terms.

2.2. Estimation Method of Model Parameters

The static panel threshold regression model was first proposed by Hansen[11]. The general fixed effect single threshold regression model can be written as follows:

\begin{equation}
y_{it} = \mu_i + \beta_1^i x_{it} I(q_{it} \leq \gamma) + \beta_2^i x_{it} I(q_{it} > \gamma) + \epsilon_{it}, i = 1, \cdots, N, t = 1, \cdots, T
\end{equation}

where the subscript \(i\) denotes the \(i\)th individual, \(t\) represents time, \(y\) is the explained variable, \(x\) denotes the explanatory variable, \(q\) indicates the threshold variable, \(I(*)\) is the indicative function, \(\mu_i\) is the individual fixed effect, and \(\epsilon_{it} \sim iid(0, \delta^2)\) is the random error term. The samples are divided into two
regimes according to the relationship between threshold variable and $\gamma$. $\beta_1$ and $\beta_2$ are the regression coefficients under the two regimes respectively. Let $x_{it}(\gamma) = \begin{cases} x_{it}(q_u \leq \gamma) \\ x_{it}(q_u > \gamma) \end{cases}$, $\beta = \begin{pmatrix} \beta_1^* \\ \beta_2^* \end{pmatrix}$, equation (5) can be simplified as:

$$y_{it} = \mu_i + \beta^* x_{it}(\gamma) + \varepsilon_{it}$$

(6)

For the individual fixed effects in equation (6), it is usually eliminated by subtracting the individual mean equation. First, the average is obtained on the individual:

$$\bar{y}_i = \mu_i + \beta^* \bar{x}_i(\gamma) + \bar{\varepsilon}_i$$

(7)

where $\bar{y}_i = \frac{1}{T} \sum_{t=1}^{T} y_{it}$, $\bar{\varepsilon}_i = \frac{1}{T} \sum_{t=1}^{T} \varepsilon_{it}$, $\bar{x}_i(\gamma) = \begin{pmatrix} \frac{1}{T} \sum_{t=1}^{T} x_{it}(q_u \leq \gamma) \\ \frac{1}{T} \sum_{t=1}^{T} x_{it}(q_u > \gamma) \end{pmatrix}$. Then subtract equation (7) from equation (6) to get the equation of eliminating the mean value:

$$Y^* = X^*(\gamma) \beta^* + \varepsilon^*$$

(8)

where $y_{it}^* = y_{it} - \bar{y}_i$, $x_{it}^*(\gamma) = x_{it}(\gamma) - x_i(\gamma)$, $\varepsilon_{it}^* = \varepsilon_{it} - \bar{\varepsilon}_i$. We can get $Y^*, X^*(\gamma)$ and $\varepsilon^*$ by heaping up individual data of each variable, such as $X^*(\gamma) = \begin{pmatrix} x_1^*(\gamma), x_2^*(\gamma), \ldots, x_n^*(\gamma) \end{pmatrix}'$.

For any given $\gamma$, the estimated value of $\beta$ is $\hat{\beta}(\gamma) = \left(X^*(\gamma)'X(\gamma)\right)^{-1}X^*(\gamma)'Y^*$, the regression residual vector is $\hat{\varepsilon}^*(\gamma) = Y^* - \hat{Y}^* = Y^* - X^*(\gamma)\hat{\beta}(\gamma)$, the residual sum of squares is:

$$S_1(\gamma) = \hat{\varepsilon}^*(\gamma)'\hat{\varepsilon}^*(\gamma) = Y^{**}\left( I - X^*(\gamma)'X(\gamma)\right)^{-1}X^*(\gamma)'Y^*$$

(9)

where $y_{it}^{**} = y_{it} - \bar{y}_i$, $x_{it}^*(\gamma) = x_{it}(\gamma) - x_i(\gamma)$, $\varepsilon_{it}^* = \varepsilon_{it} - \bar{\varepsilon}_i$. We can get $Y^*, X^*(\gamma)$ and $\varepsilon^*$ by heaping up individual data of each variable, such as $X^*(\gamma) = \begin{pmatrix} x_1^*(\gamma), x_2^*(\gamma), \ldots, x_n^*(\gamma) \end{pmatrix}'$.

When equation (9) reaches the minimum, the corresponding $\hat{\gamma}$ is the estimated value of $\gamma$, written $\hat{\gamma} = \arg\min_{\gamma} S_1(\gamma)$. If the selection range is wide in the process of determining $\gamma$, we can sort $q_u$ in ascending order, remove the values of $\eta\%$ range of the head and tail, then determine $\gamma$ in the remaining $q_u$. In the empirical process, $\eta\%$ is usually taken as 5%.

2.3. Model Test and Determination of Threshold Number

The original hypothesis and alternative hypotheses corresponding to test whether there is threshold effect for a single threshold model are: $H^0_0: \beta_1 = \beta_2$, $H^1: \beta_1 \neq \beta_2$.

The original hypothesis shows that there is no threshold effect in the single threshold model, let $S_0$ denote the residual sum of squares; the alternative hypothesis shows that the model is single threshold model, let $S_1$ denote the residual sum of squares. The F test statistic is: $F_1 = \left[ S_0 - S_1(\hat{\gamma}) \right] / \hat{\sigma}^2$. The
asymptotic distribution of \( F_1 \) obeys the chi-square distribution, which depends on sample selection, so it is difficult to determine the critical value.

Hansen[10] proposed to use LR statistic:
\[
\text{LR}_i (\gamma) = \frac{\left( S_i (\gamma) - S_i (\hat{\gamma}) \right) \sigma_i^2}{\hat{\gamma} - \gamma},
\]
where \( S_i (\gamma) \) and \( S_i (\hat{\gamma}) \) indicate the real value and estimated value of the residual sum of squares in equation (8) respectively. The original hypothesis \( H_0: \gamma = \gamma_0 \) of likelihood ratio test corresponds to \( H_0: \beta_1=\beta_2, \gamma_0 \) is the actual value of threshold variable. There is no threshold effect when the original hypothesis is true. The asymptotic distribution of \( \text{LR}_i (\gamma_0) \) derived by Hansen can be used to construct the effective asymptotic confidence interval of threshold estimation and calculate its acceptance domain \( c(\alpha) \). The original assumption \( H_0: \gamma = \gamma_0 \) is not rejected when \( \text{LR}_i (\gamma_0) \leq c(\alpha) \) and \( c(\alpha) = 2 \ln \left( 1 - \sqrt{1 - \alpha} \right) \).

After checking there is at least one threshold, it is necessary to determine whether there are two or more thresholds. Fitting the residual sum of squares of the double threshold regression model is \( S_2(\gamma_2) \), and the second threshold is \( \hat{\gamma}_2 = \arg \min_{\gamma_2} \{ S_2 (\gamma_2) \} \).

Testing the original hypothesis and alternative hypotheses: \( H_0^2: \) there is only one threshold, \( H_1^2: \) there are two thresholds; LR statistic is \( \text{LR}_2 (\gamma) = \frac{\left( S_2 (\gamma) - S_2 (\hat{\gamma}_2) \right) \sigma^2}{\hat{\gamma}_2 - \gamma} \). \( H_0^3: \) there are two thresholds, \( H_1^3: \) there are three thresholds; LR statistic is \( \text{LR}_3 (\gamma) = \frac{\left( S_3 (\gamma) - S_3 (\hat{\gamma}_3) \right) \sigma^2}{\hat{\gamma}_3 - \gamma} \). The test method is as same as the test method for single threshold, and the number of threshold values in the model can be determined by analogy.

3. Empirical Analysis

3.1. Model Setting and Data Description

3.1.1. Construction of Threshold Regression Model. It is necessary to implement the panel unit root test, panel cointegration test and model setting test of the data for each variable before fitting threshold model. The test results show that there is a significant cointegration relationship between explained variables and explanatory variables; the results of Hausman test \( (\chi^2 = 13.3422, P=0.0204) \) and likelihood ratio test \( (F=25.8834, P=0.0000) \) indicate that we should select the fixed effects model to fit the sample data. In order to test the asymmetric effect of economic growth on CO₂ emission of construction industry, this paper selects \( \ln CO₂ \) as the explained variable, \( \ln PGDP \) as the threshold variable and the core explanatory variable. The general mathematical expression of static panel threshold regression model after subtracting mean value is as follows:

\[
\ln CO₂ = \beta_1 \ln PGDP \times I(\gamma \leq \gamma_j) + \sum_{j=2}^{k-1} \beta_j \ln PGDP \times I(\gamma_j < \gamma \leq \gamma_{j+1}) + \beta_1 \ln PGDP \times I(\gamma > \gamma_k) + X_u \theta + e_u,
\]

where \( \gamma \) indicate the threshold variable, \( X_u = (\ln POP, \ln ENE, \ln ENS, \ln I/S) \) is a set of control variables, \( \theta = (\theta_1, \theta_2, \theta_3, \theta_4) \) represent the regression parameters corresponding to control variables, \( k \) is the number of threshold and needs to be determined by hypothesis test in empirical study.

3.1.2. Data Source and Description. The sample data set of this paper is the panel data from 30 provinces in Chinese mainland during 1997-2015. Taiwan, Macao, Hong Kong and Tibet are not included in the study due to the serious lack of related data. Based on China Emission Accounts and Datasets, we collected the data of total CO₂ emissions from construction industry. The data of energy structure are derived from China Energy Statistics Yearbook (1998-2016). Moreover, the data on population size, industry scale, energy efficiency and per capita GDP are obtained from China Statistics Yearbook (1998-2016) and 30 Provincial Statistical Yearbook (1998-2016). The definitions and the statistical description of all variables are shown in Table 1.
Table 1. Definition and statistical description of variables in the model (10).

| Variable | Definition          | Units     | Min | Mean   | Max     | Std.dev. |
|----------|---------------------|-----------|-----|--------|---------|----------|
| CO₂      | Total CO₂ emission | 10⁴ tons  | 10  | 139.16 | 2220    | 154.05   |
| POP      | Population size     | 10⁴ people| 280 | 4258.23| 10849   | 2670.43  |
| PGDP     | Per capita GDP      | Yuan      | 2250| 19985.62| 79255.90| 5715.89  |
| ENE      | Energy efficiency   | 10⁴ yuan per tce | 0.6924| 15.70| 109.30 | 14.89 |
| ENS      | Energy structure    | %         | 0.31| 20.46 | 99.90   | 19.19    |
| IS       | Industry scale      | %         | 3.25| 6.73  | 14.03   | 1.86     |

3.2. Empirical Results
In this study, we used the package `xtptm` in Stata12.0 to set the single threshold, double threshold and three threshold regression model in turn to test the significance of the threshold effect in model (10). The results of threshold effect tests are shown in Table 2.

Table 2. Results of threshold effect tests.

| Hypothesis testing | LR statistics | Critical value of Bootstrap (1000 times) |
|--------------------|---------------|----------------------------------------|
| H₀: there is no threshold | 15.0354* | 2.88 | 3.892 | 7.703 |
| H₀: there is only one threshold | 6.6346* | -2.054 | -0.536 | 4.307 |
| H₀: there are two thresholds, H₁: there are three thresholds | 4.9593 | 2.461 | 3.617 | 6.227 |

Remark: * indicates significant at 1% significance level.

We can see that the LR statistics of single threshold and two thresholds regression model reject original hypothesis at 1% significance level, and the LR statistic of three thresholds regression model doesn’t reject original hypothesis at 1% significance level, so we select double threshold regression model. We got the estimated values of two thresholds are: \( \gamma_1 = 9.1435 \), \( \gamma_2 = 9.2685 \), and the 95% asymptotic confidence intervals of \( \gamma_1 \) and \( \gamma_2 \) are [8.5688, 10.0431] and [8.3939, 10.8677] respectively. The static panel two thresholds regression model of this empirical study is as follows:

\[
\ln CO_2 = \beta_1 \ln PGDP \times I(\gamma \leq 9.1435) + \beta_2 \ln PGDP \times I(9.1435 < \gamma \leq 9.2685) + \beta_3 \ln PGDP \times I(\gamma > 9.2685) + \theta_1 \ln POP + \theta_2 \ln ENE + \theta_3 \ln ENS + \theta_4 \ln IS + \varepsilon
\] (11)

The parameter estimation results of the model (11) are shown in Table 3.

Table 3. Results of parameter estimation for the two thresholds model.

| Variable                  | Coefficients | Estimates | Std  | t values (p values) |
|---------------------------|--------------|-----------|------|---------------------|
| lnPGDP × I (\( \gamma \leq 9.1435 \)) | \( \beta_1 \) | 1.2436*** | 0.074 | 16.7968 (0.0000)    |
| lnPGDP × I (9.1435 < \( \gamma \leq 9.2685 \)) | \( \beta_2 \) | 1.2732*** | 0.0714 | 17.8262 (0.0000)    |
| lnPGDP × I (\( \gamma > 9.2685 \)) | \( \beta_3 \) | 1.2231*** | 0.0673 | 18.1658 (0.0000)    |
| lnPOP                     | \( \theta_1 \) | 0.1677*   | 0.0871 | 1.9247 (0.0548)     |
| lnENE                     | \( \theta_2 \) | -0.7138*** | 0.0475 | -15.0381 (0.0000)   |
| lnENS                     | \( \theta_3 \) | 0.0782**  | 0.0396 | 1.9760 (0.0487)     |
| lnIS                      | \( \theta_4 \) | 0.1470*   | 0.0715 | 0.8569 (0.0919)     |

Remark: ***, * indicates a significant at 1% and 10% significance level respectively.

3.3. Result Analysis
Based on the two thresholds regression model (11) and the results of parameter estimation in Table 3, we can make the following analysis:
Population size, industrial scale and energy structure have a positive impact on CO₂ emission from construction industry. The elasticity of ln\(POP\) is 0.1677. That is to say a 1% growth in industrial scale would generate 0.1677% increase in CO₂ emissions from China's construction industry when other factors remain constant. Generally speaking, the increase in the population size will lead to the enhancement of human economic activities, which will further promote the demand for transportation, housing, infrastructure construction, resulting in increased consumption of building materials and energy, and then the CO₂ in the construction industry will increase. Industrial scale has a positive relationship with CO₂ emission of construction industry. A 1% increase in industrial scale lead to 0.1470% increase in CO₂ emissions from China's construction industry when other influencing factors remain constant. As for industry scale effect, there is no doubt that the development of the construction sector requires the consumption of large amounts of construction materials such as steel, aluminum, cement and glass products. This will lead to increased CO₂ emissions in the construction industry inevitably. Energy structure is significant with a coefficient of 0.0782, which indicates that the proportion of coal consumption in the construction industry to its total energy consumption increased by 1%, resulting in an increase of 0.372% in CO₂ emissions from the construction industry. The positive effect of energy structure on CO₂ emission of construction industry is relatively small compared with other variables. The reason may be that the main source of CO₂ emission from construction industry is high pollution building materials, while coal is mainly used for thermal power generation, accounting for small proportion of total energy consumption. The coefficient of ln\(ENE\) is negative significantly, which means that the development of energy-saving technology is the main way to reduce the CO₂ emissions of construction industry. A 1% growth in energy efficiency lead to 0.7138% reduce in CO₂ emission of construction industry. The number of R&D personnel and the R&D investment are increasing year by year according to China Science and Technology Statistics Yearbook. Increasing R&D efforts can improve the technical methods and optimize the process steps of construction effectively. In addition, stepping up efforts of R&D can also promote the use of environmental protection building materials. All of these will reduce energy consumption in the construction process effectively and further decrease the CO₂ emissions of construction industry.

The sample data in this study can be divided into three sections according to the results of threshold effect test and threshold estimates: low-speed economic growth zone (ln\(PGDP\) ≤ 9.1435), medium-speed economic growth zone (9.1435 < ln\(PGDP\) ≤ 9.2685) and high-speed economic growth zone (ln\(PGDP\) > 9.2685). We find that the estimates of \(\beta_1\), \(\beta_2\) and \(\beta_3\) are all positive and larger than other control variables significantly, which means that ln\(PGDP\) has a positive impact on CO₂ emissions of construction industry in three zones of economic growth, economic activities are a major driver of CO₂ emissions, and there is an asymmetric relationship between them. The elasticity coefficient of ln\(PGDP\) is 1.2436 when the economy is in the low-speed growth area, which means that the CO₂ emission of construction industry will increase by 1.2436% for every 1% increase of per capita GDP; the positive effect on the CO₂ emissions of construction industry is the strongest when the economy is in the medium-speed growth zone; and the effect of economic activities is weakened to 1.2231, which is the lowest of the three zones. This interesting phenomenon is related to China’s national conditions. In the low-speed economic growth zone, local governments mainly rely on large-scale fixed asset investment to drive economic growth. The continuous expansion of fixed asset investment stimulates the development of the construction industry, resulting in a large amount of consumption of high emission building materials and coal. Therefore, the positive effect of economic growth on the CO₂ emissions of the construction industry in this zone is large. In the medium-speed economic growth zone, the mode of economic growth still mainly depends on fixed asset investment and the scale has been expanded. In addition, the development of energy saving and emission reduction technology is poor, so the elasticity coefficient corresponding to this zone is the largest. In the high-speed economic growth zone, the government actively optimizes the economic structure to maintain the sustainable economic growth, and with the continuous progress of energy saving technology, the impact of economic growth on the CO₂ emissions of the construction industry is gradually decreasing.
4. Conclusions and Policy Implications

In this paper, panel threshold regression model is used to study the main influencing factors and their effects of CO₂ emissions in China’s construction industry. Furthermore, the asymmetric influence of economic growth on CO₂ emissions from the construction industry was discussed in detail. The results show that population size, industrial scale and energy structure have positive impacts on CO₂ emissions from construction industry, while energy efficiency has a significant negative impact. After controlling the above factors, economic growth has a non-linear influence mechanism on the CO₂ emission of construction industry and shows the characteristics of two thresholds. Besides, economic activities show a positive effect under the three intervals of economic growth. As the economic level crosses two thresholds, the positive effect of economic growth on the CO₂ emissions in construction industry shows the characteristics of increasing first and then decreasing accordingly.

Based on the results, we have found the effective way for low-carbon development of construction industry: (1) The government should pay attention to the nonlinear effects of economic development on carbon emissions from the construction industry at different stages, strive to realize the transformation of economic growth from fixed asset investment to technological innovation and optimize economic growth performance. (2) The government and construction enterprises should encourage the development of energy conservation and emission reduction technologies, and take flexible and effective measures to improve energy efficiency. (3) The government should actively promote the upgrading of industrial structure and carry out the circular economy mode in the construction industry, strengthen the treatment of high pollution, high energy consumption and substandard construction enterprises, promote the development of green buildings.

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