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Which Provinces Should Pay More Attention to CO_2 Emissions in China's Construction Industry?

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Abstract. Construction industry has existed the problems of high investment and pollution. As a big country in the construction industry, China has a vast territory and the CO_2 emissions of the construction industry vary greatly among different regions. So which provinces should pay more attention to the CO_2 emissions of the construction industry is a question worthy of consideration. Based on the provincial panel data of China from 1997 to 2015, this paper extends the STIRPAT model and empirically analyses the impact of influencing factors in different quantiles by using quantile regression panel model. Research results show that: (1) The effect of population size, economic growth, energy structure and industrial scale on CO_2 of construction industry in different quantiles are positive, while the effect of energy efficiency is negative. (2) The effect of population size on CO_2 emissions in the 50th-75th quantile provinces is greater than those in the other quantile provinces; the impact of economic growth in the 10th-25th quantile provinces is higher than those in the other percentile provinces; the influence of energy structure in the 25th-50th and 50th-75th quantile provinces are stronger than those in the other quantile provinces; the influence intensity of industry scale in the upper 90th quantile provinces is the highest in all the quantile provinces; the effect of energy efficiency in the upper 90th quantile provinces is lower than those in the other percentile provinces. According to these results, we put forward some corresponding policy suggestions.

1. Introduction

Greenhouse gas emissions has become a main course of global warming and environmental pollution, and the carbon dioxide (CO_2) accounts for about 70% of the greenhouse gas. China is the largest CO_2 emitter in the world at present, its total emissions of CO_2 have reached 9232.6 million tons in 2017, 1.81 times that of the United States. With the increasing international pressure, China has become the focus of a global plan to reduce carbon emissions. According to the data provided by the World Bank, in order to achieve the goal of energy saving and emission reduction by 2030, 70% of the potential emission reduction in construction industry. Therefore, it is of great practical significance to study the main driving forces of CO_2 emissions in China's construction industry for formulating effective environmental protection and emission reduction strategies.

In recent years, scholars have conducted a large number of studies on the main driving forces of CO_2 emissions in the construction industry with people's attention to environmental pollution and energy consumption, and achieved fruitful results. We can find that the main methods to study on the influencing factors of CO_2 emissions in the construction industry include life cycle assessment method[1-3], input-output method[4-5], decomposition method[6] and so on. These traditional methods based on mean regression to study CO_2 emissions in construction industry. However, the economic variables are often non-normal distributed, and the tail of distributions hide important information. We know that the quantile regression does not need to assume zero-mean, homoscedasticity and normal distribution of stochastic error term, it can reduce the limitation of residual distribution and the quantile estimators are more effective than the OLS estimators when disturbance items are not normal[7]. Beyond that, the quantile regression can reflect the influence of the change of independent variables on the whole conditional distribution of dependent variable and estimate different parameter values at different quantile levels of dependent variable compared with the OLS method. Third, the quantile regression is monotonous and homogeneous, which can transform the unstable sample data in the regression process without affecting the estimation effect. Last, the quantile regression estimates parameters by minimizing the sum of absolute weighted residuals and it is less sensitive to outliers and more robust in parameter estimation. In order to overcome the shortcomings of the existing research methods, this paper will apply the quantile regression model to investigate the impacts of the influencing factors of CO_2 emissions in China's construction industry under different level of CO_2 emissions with a provincial panel data of China during the period of 1997-2015.

2. Model and Methodology Specification

2.1. Quantile Regression Model

The quantile regression method was first proposed by Koenker and Bassett[8]. Regression for independent variable X based on conditional quantile of dependent variable Y, and the regression models under all quantiles are obtained. The mathematical expression of the quantile regression model is as follows:

$$y_i = x_i'\beta_\theta + \mu_{\theta i}, 0 < \theta < 1 \tag{1}$$

$$Quant_\theta(y_i \mid x_i) = x_i'\beta_\theta \tag{2}$$

where y denotes the dependent variable, x is a vector of the explanatory variable, μ denotes the random error term, whose conditional quantile distribution is equal to zero. $Quant_\theta(y_i \mid x_i)$ is the θth quantile of the dependent variable.

The estimator of regression coefficients in the quantile θ is $\hat{\beta}_\theta$ which satisfies:

$$\hat{\beta}_\theta = \arg\min_\beta \sum_{y_i \ge x_i'\beta} \theta\left|y_i - x_i'\beta\right| + \sum_{y_i < x_i'\beta} (1-\theta)\left|y_i - x_i'\beta\right| \tag{3}$$

Different parameter estimates can be obtained by giving different θ values. We use the linear programming to solve the problem of (3), and apply the bootstrap method to estimate the standard deviation and confidence interval of the parameters in the quantile regression.

The quantile regression model is quite different from the traditional segmental regression method. The traditional segmental regression estimates parameters based on subset of samples, while the quantile regression estimates the parameters of different quantiles using all sample data[9]. Koenker[10] discussed the details of the quantile regression methods.

2.2. Construction of Empirical Model

IPAT model was first proposed by Ehrlich and Holdren[11] to reflect the impact of population on environmental stress. The mathematical expression of the model is as follows:

$$I = P \cdot A \cdot T \tag{4}$$

where I, P, A and T indicate the pollution intensity of a pollutant, the population size, the economic development level of a country and the technology development level respectively.

Although the IPAT model is concise and intuitive, it also has some limitations. First, the IPAT assumes that the elasticity coefficients of the impact of population size, economic prosperity and technological level on the environment are consistent, which conflicts with the environmental Kuznets curve hypothesis. Second, the unity of the dimensions on both sides of the equation limits other factors that may affect environmental pressure. Third, the hypothesis testing unable to proceed[12]. In order to overcome the above limitations, this paper adopts the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model, which based on the IPAT model and proposed by Dietz and Rosa[13]:

$$I_t = aP_t^b A_t^c T_t^d \xi_t \tag{5}$$

where *a* represents the intercept term; *I*, *P*, *A* and *T* are the same as in equation (4); *b*, *c* and *d* represent the elastic coefficients of environmental effects with respect to *P*, *A* and *T* respectively, ξ_t is the random error term; since the model is used for annual data analysis, subscript *t* depicts the year. In order to eliminate possible heteroscedasticity, all variables are logarithmic processed. The sample data set is the panel data, so the equation (5) after logarithmic transformation can be written as follows:

$$\ln I_{it} = \ln a + b\left(\ln P_{it}\right) + c\left(\ln A_{it}\right) + d\left(\ln T_{it}\right) + e_{it} \tag{6}$$

combined with this study and considered the actual situation of China's construction industry, we further expand the STIRPAT model to the following form:

$$\begin{aligned} \ln CO_{2it} = \ln a + \beta_1 \ln POP_{it} + \beta_2 \ln PGDP_{it} + \beta_3 \ln ENE_{it} \\ + \beta_4 \ln ENS_{it} + \beta_5 \ln IS_{it} + e_{it}. \end{aligned} \tag{7}$$

where the CO_2 (10,000 tons) represents the CO_2 emissions of the construction industry of each province; *POP* (10,000 people) is the total population size of each province at the end of the year; *PGDP* (yuan) is economic growth and is represented by GDP per capita of each province which is converted into constant prices (1997=100) to cut the effects of inflation; *ENE* (10,000 yuan per tce) is energy efficiency, which is used to measure the technical development level of the construction industry, represents the actual output of the unit energy consumption in the construction industry; *ENS* is calculated by dividing coal consumption in the construction industry by its total energy consumption; *IS* reflects the scale effect of construction industry and is calculated by added value of construction industry divided by GDP; *a* and *e* are the intercept and disturbance terms, respectively. The panel regression model (7) can carry out mean regression on the influencing factors of CO_2 emissions in China's provincial construction industry. In the actual economic problems, the CO_2 emissions and the influencing factors may not follow the normal distribution. In order to study the impact of various factors on CO_2 emissions from China's construction industry in different quantiles, we introduce quantiles into the model (7) and obtain the econometric model for empirical analysis:

$$\begin{aligned} Q_\tau(\ln CO_{2it}) = (\ln a)_\tau + \beta_{1\tau} \ln POP_{it} + \beta_{2\tau} \ln PGDP_{it} \\ + \beta_{3\tau} \ln ENE_{it} + \beta_{4\tau} \ln ENS_{it} + \beta_{5\tau} \ln IS_{it}, \end{aligned} \tag{8}$$

where $Q(\ln CO_{2it})$ and $(\ln a)_\tau$ represent τth quantile in the dependent variable and constant term respectively. $\beta_{1\tau}$, $\beta_{2\tau}$, $\beta_{3\tau}$, $\beta_{4\tau}$ and $\beta_{5\tau}$ indicate the regression parameters of τth quantile in the explanatory variables.

3. Data Source and Description

The variables involved in model (8) are panel data of 30 provinces, municipalities and autonomous regions in China's mainland from 1997 to 2015. Due to the lack of relevant variable data in Tibet, it is not included in the sample. Provincial construction industry CO_2 emissions data is collected from CEADs; the data of coal consumption is from China Energy Statistics Yearbook (1998-2016); the other explanatory variables data sets are from China Statistics Yearbook (1998-2016) and 30 Provincial Statistical Yearbook (1998-2016). The definitions and statistical description of all the variables in this study are shown in Table 1.

Table 1. Definition and statistical description of variables in the model (8)

Variable	Definition	Units of measurement	Mean	Std.dev.	Min	Max
CO_2	Total CO_2 emission	10,000 tons	139.16	154.05	10	2220
POP	Population size	10,000 people	4258.23	2670.43	280	10849
PGDP	Per capita GDP	Yuan	19985.62	5715.89	2250	79255.90
ENE	Energy efficiency	10,000 yuan per tce	15.70	14.89	0.6924	109.30
ENS	Energy structure	Percent	20.46	19.19	0.31	99.90
IS	Industry scale	Percent	6.73	1.86	3.25	14.03

4. Empirical Results

4.1. Test of Multicollinearity

In this paper, Klein's method [14] is used to examine the multicollinearity test. From the results of likelihood ratio test (F = 25.8834, P = 0.0000) and Hausman test (χ^2 = 13.3422, P = 0.0204), we can see that the fixed effect panel regression model should be used to fit the sample data and obtains R^2=0.602. The correlation coefficient matrix of explanatory variables in this paper is shown in Table 2. As can be seen from Table 2, the absolute value of correlation coefficients of each explanatory variable is less than R^2, which shows that the correlation between explanatory variables will not cause multicollinearity problems in the model, and all variables are suitable for regression estimation.

Table 2. The correlation coefficient matrix

	ln*POP*	ln*PGDP*	ln*ENE*	ln*ENS*	ln*IS*
ln*POP*	1.00	-0.03	0.25	-0.10	-0.36
ln*PGDP*	-0.03	1.00	0.39	-0.46	-0.25
ln*ENE*	0.25	0.39	1.00	-0.25	-0.14
ln*ENS*	-0.10	-0.46	-0.25	1.00	0.10
ln*IS*	-0.36	-0.25	-0.14	0.10	1.00

4.2. Unit Root Test and Co-integration Test

We applied the Levin-Lin-Chu (LLC) to implement the panel unit root test, and the results are shown in Table 3. It can be seen that all variables are non-stationary at the 1% significance level, but their first order difference series are stationary, it indicates that the variables in this study are first order single integration. Further, we implemented panel co-integration test to examine whether there is a long-term equilibrium relationship between the CO_2 emissions of the construction industry and its main driving forces. In KAO panel test, ADF = -6.123 and P = 0.0000, which rejects the primitive hypotheses that there is no co-integration relationship. The results are indicative of a significant co-integration relationship between the dependent variable and the explanatory variables.

Table 3. Results of panel unit root tests

Variable	Test form	Test statistic	Results	First difference	Test form	Test statistic	Results
$\ln CO_2$	(0, 0)	5.85	non-stationary	$\Delta\ln CO_2$	(C, T)	-17.09***	stationary
ln*POP*	(0, 0)	11.62	non-stationary	Δln*POP*	(C, T)	-11.10***	stationary
ln*PGDP*	(C, T)	4.48	non-stationary	Δln*PGDP*	(C, T)	-2.52***	stationary
ln*ENE*	(0, 0)	4.87	non-stationary	Δln*ENE*	(C, T)	-12.65***	stationary
ln*ENS*	(C, 0)	-0.62	non-stationary	Δln*ENS*	(C, T)	-18.86***	stationary
ln*IS*	(0, 0)	4.68	non-stationary	Δln*IS*	(C, T)	-13.12***	stationary

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Remark: The optimal lag is based on the Akaike Information criterion (AIC) and Schwartz information criterion (SC). ***, **, * indicates a significant at 1%, 5% and 10% significance level respectively. In the Test form, 0, C and T represent constant, intercept and trend items respectively.

4.3. Normal Distribution Tests

We tested the normality of all variables before regression analysis through the Q-Q plot, and the results are shown in Figure 1 (a-f). The observed values of all variables deviate from the straight line, indicating that all variables do not conform to the normal hypothesis. Accordingly, OLS regression can’t reveal the important information contained in the tail of the data comprehensively, which further proves that it is reasonable to use quantile regression model for empirical analysis.

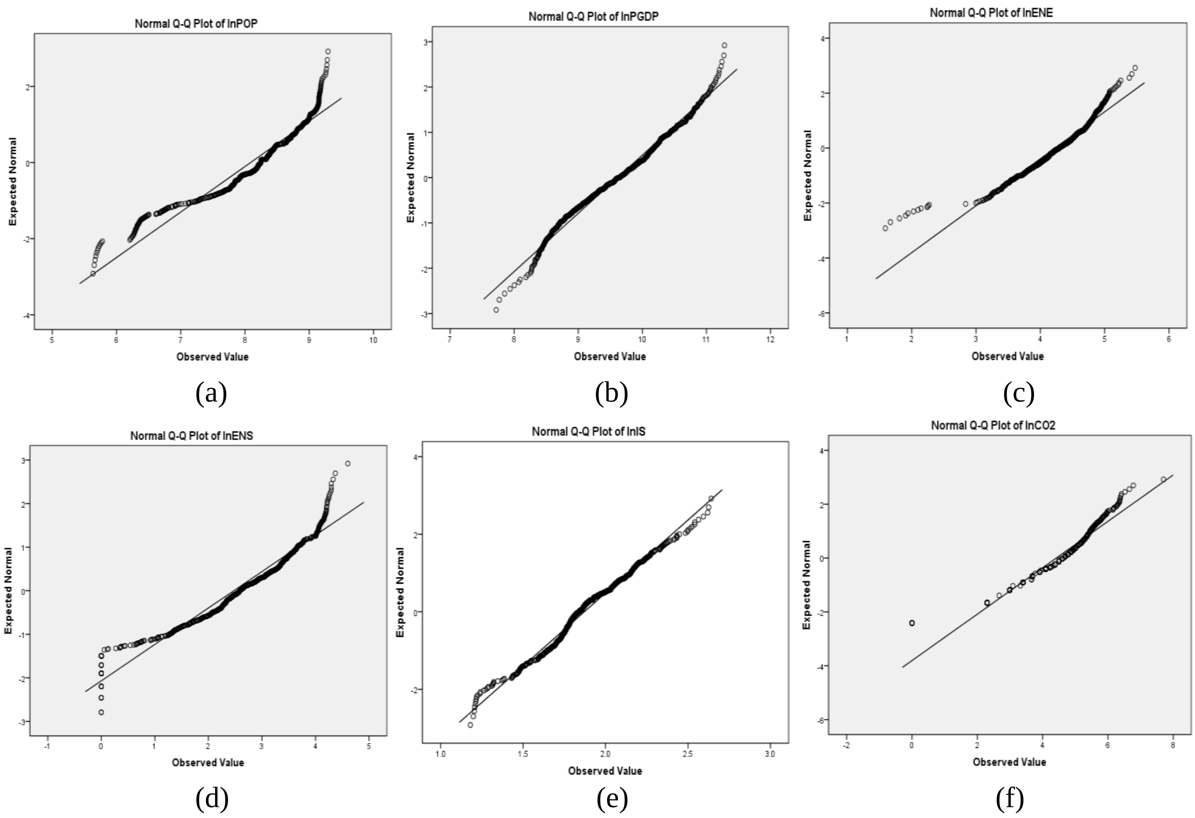

Figure 1. Normal Q-Q plots of ln*POP*, ln*GDP*, ln*ENE*, ln*ENS*, ln*IS* and lnCO_2 respectively

4.4. Quantile Regression Results Analysis

Quantile regression can directly reveal the marginal impact of explanatory variables on CO_2 emissions of different quantiles in construction industry. Different quantile functions can be obtained under different quantiles, which can reveal the influence of the main driving forces on the dependent variables of corresponding quantiles. Therefore, five representative quantiles (10, 25, 50, 75 and 90) are selected for quantile regression, and the estimation results are analyzed in depth. According to annual average CO_2 emissions of China's construction industry from 1997 to 2015, 30 provinces in China are divided into six groups (Table 4). It can be seen from table 4 that although the economic development of some provinces is quite different, the annual CO_2 emissions of the construction industry have little change.

Table 4. Provincial distribution in term of CO_2 emissions in the construction industry

Quantile	Province
The lower 10th quantile group	Heilongjiang, Guangxi, Hainan
The 10th-25th quantile group	Jiangsu, Jiangxi, Guizhou, Qinghai, Ningxia
The 25th-50th quantile group	Beijing, Hebei, Henan, Guangdong, Chongqing, Gansu, Xinjiang
The 50th-75th quantile group	Tianjin, Shanxi, Liaoning, Anhui, Fujian, Sichuan, Yunnan, Shannxi
The 75th-90th quantile group	Inner Mongolia, Jilin, Shanghai, Hunan
The upper 90th quantile group	Zhejiang, Shandong, Hube

Table 5. Estimation results: quantile regression panel model and fixed effects linear panel OLS model during the period of 1997-2015

Variables	Quantile regressions					OLS
	10th quant	25th quant	50th quant	75th quant	90th quant	
Intercept	-11.535***	-13.040***	-13.144***	-12.708***	-9.948***	-12.583***
ln*POP*	0.546***	0.634***	0.722***	0.721***	0.446***	0.587***
ln*PGDP*	1.274***	1.301***	1.216***	1.224***	1.070***	1.315***
ln*ENE*	-0.947***	-0.775***	-0.655***	-0.677***	-0.409**	-0.762***
ln*ENS*	0.295***	0.332***	0.355***	0.321***	0.310***	0.320***
ln*IS*	0.034	0.258*	0.423***	0.391***	0.799***	0.361***

Remark: ***, **, * indicates a significant at 1%, 5% and 10% significance level respectively.

The estimation results of quantile regression are shown in Table 5 and Figure 2. We give the estimation results of OLS in Table 6 for comparative analysis. From Table 5, it can be seen that most of the parameter estimation results of the influencing factors are significant at the 10% test level. The regression coefficients of ln*POP*, ln*GDP*, ln*ENS* and ln*IS* are all positive, indicating that population size, economic growth, energy consumption structure and industrial scale have a positive impact on CO_2 emissions of construction industry; the regression coefficients of ln*ENE* are estimated to be negative, indicating that technological level effectively inhibits the growth of CO_2 emissions of construction industry. In addition, the elasticity coefficient of ln*PGDP* is the largest in all quantiles, indicating that economic growth is the main factor affecting CO_2 emissions in construction industry, and population size and energy consumption structure have a greater impact. Especially, the results of parameter estimation of ln*IS* are not significant in low quantiles, indicating that industrial scale only has more influence on the provinces where CO_2 emissions in construction industry are in the middle and high quantiles. From Figure 2, we can see that the parameters trends of ln*POP* and ln*ENS* up first and then down with the increase of quantiles, ln*PGDP* down, and ln*ENE* and ln*IS* up. These show that the effects of the influencing factors of CO_2 emissions in construction industry are heterogeneous, and several interesting phenomena of quantile regression results are discussed below.

The effects of population size on CO_2 emissions in the 50th-75th quantile provinces are greater than those in the other quantile provinces, which may be caused by the different annual growth rate of population in different regions. Generally speaking, the increase of population will promote the construction demand of housing, transportation, infrastructure and so on, which will lead to the increase of energy and building materials consumption, and CO_2 from the construction industry will increase. The larger the population, the stronger the human economic activity will be, which will further lead to an increase in CO_2 emissions from the construction industry. Due to the implementation of the national policy of Family Planning, the population growth rate in all regions of China has been at a low level in recent years. According to the relevant data of China Statistical Yearbook, the annual average population growth rate during 1997-2015 period in the 50th-75th quantile provinces is 1.16%, is far larger than those in the lower 10th quantile provinces (0.46%), the 10th-25th quantile provinces (0.64%), 25th-50th quantile provinces (-0.86%), 75th-90th quantile provinces (0.92%) and upper 90th quantile provinces (0.61%). Therefore, the impact of population size on CO_2 emissions from construction industry in the 50th-75th quantile provinces is stronger than those in the other quantile provinces.

The influence of economic growth on CO_2 emissions of construction industry shows a downward trend with the increase of quantile, and the provinces with 10th-25th quantile CO_2 emissions of construction industry have the greatest impact, which may be caused by the different proportion of fixed-asset investment in construction industry in the whole society of the region. Infrastructure construction is the premise of economic development. Therefore, investment in fixed assets has always been greatly supported by central and all levels governments as one of the important strategic industries that promote economic development. However, the large-scale investment in fixed assets has driven the rapid development of the construction industry, consumed a large number of steel, cement and fossil fuels, and produced a large number of CO_2 emissions. After calculating the annual average growth rate of fixed assets investment in construction industry in 1997-2015 based on China Statistical Yearbook, we found that the annual average growth rate of fixed assets investment in the 10th-25th quartile provinces is higher than those in other quartile provinces. The rapid growth of fixed assets investment leads to the high annual growth rate of energy consumption in construction industry, and the annual growth rate of CO_2 emissions in construction industry also increases. Therefore, the impact of economic growth on CO_2 emissions in construction industry in 10th-25th quantile provinces is greater than those in other quantile provinces.

The inhibition of energy efficiency on CO_2 emissions from construction industry in the upper 90th quantile provinces are less than those in the other quantile provinces. This may be related to the difference of patent technology level, R&D investment and the number of R&D personnel in different regions. With the development of new technologies such as energy saving and emission reduction, energy efficiency plays an increasingly prominent role in improving the environment and enhancing the competitiveness of enterprises. On the one hand, patents can protect technological R&D achievements effectively, and encourage enterprises to expand investment in technological R&D. Relevant data from China Science and Technology Statistics Yearbook show that the average annual growth rate of patents granted in the upper 90th quantile provinces during 1997-2015 is lower than those of other quantile provinces. The slow growth in the number of patents has led to the slow progress of technological level in provinces with CO_2 emissions above 90th quantile compared with other quantile provinces. On the other hand, the R&D of new technology needs a lot of R&D funds and R&D personnel. Therefore, R&D funds and R&D personnel determine the level of energy efficiency. We found that annual growth rate of R&D investment and R&D personnel of R&D institutions in the upper 90th quantile provinces during 1997-2015 is much lower than those in other quantile provinces based on China Statistical Yearbook. The slow growth of R&D investment and R&D personnel is also one of the reasons for the slow technological progress in the upper 90th quantile provinces. The slow progress of energy saving and emission reduction technology results in energy efficiency has less inhibition on CO_2 emissions of provinces in the upper 90 quantile compared with other quantile provinces.

The elasticity coefficient of energy structure in the median is the largest, which has a higher impact on the construction industry in the 25th-50th and 50th-75th quantile provinces than other percentile provinces. This may be due to the difference in the proportion of coal consumption to the total energy consumption of construction industry in different provinces. China is currently the largest producer and consumer of coal in the world. Coal is rich in reserves and low in price, which has become the main source of energy consumption in China. Because coal combustion produces a large amount of CO_2, coal consumption accounts for a significant proportion of total energy consumption, which will inevitably increase the CO_2 emissions of the construction industry. We identified that the annual average proportion of coal consumption in total energy consumption of provinces in 25th-50th and 50th-75th quantile during 1997-2015 is higher than those of provinces in the other quantile based on China Energy Statistics Yearbook. Therefore, the impact of energy structure on CO_2 emissions from construction industry in 25th-50th and 50th-75th quantile provinces is greater than that of other quantile provinces.

The impact of industrial scale on CO_2 emissions of construction industry shows an upward trend with the increase of quantile. The elasticity coefficient in 90th quantile is greater than that of 10th, 25th, 50th and 75th quantile, which is mainly due to the differences of construction industry scales in different province. The construction industry is a production sector specializing in civil engineering, housing construction and equipment installation, such as factories, railways, bridges, ports, roads and public infrastructure construction. The development of the construction industry needs to consume a lot of building materials, such as steel, cement, aluminum and glass products. The large consumption of these building materials will inevitably lead to a large amount of CO_2 emissions in the construction industry. According to the China Statistical Yearbook, the average annual output value of the construction industry of the upper 90th quantile provinces in 1997-2015 is 518.294 billion yuan, and those in the lower 10th, 10th-25th, 25th-50th, 50th-75th and 75th-90th quantile provinces are 69.363 billion yuan, 22.632 billion yuan, 216.258 billion yuan, 196.976 billion yuan and 162.932 billion yuan respectively. We can see that the scale of construction industry in the upper 90th quantile provinces are much larger than those in other percentile provinces. Therefore, the impact of industrial scale on CO_2 emissions of construction industry in the upper 90th quantile provinces is stronger than those of other percentile provinces.

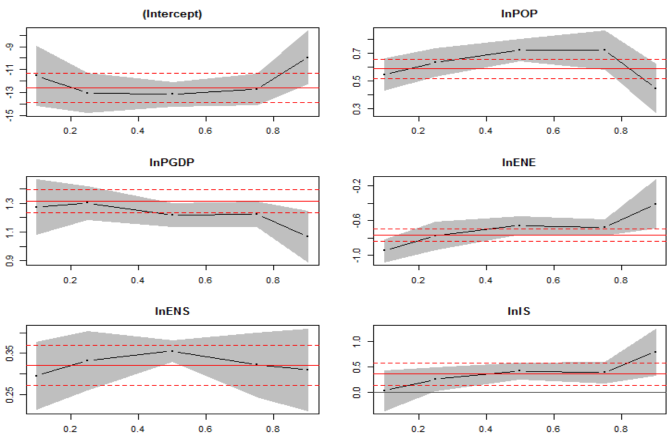

Figure 2. The effects of influencing factors on the CO_2 emissions in construction industry

Remark: Shaded areas represent 95% confidence bands for the quantile regression estimates. The horizontal dotted lines depict the 95% confidence intervals for the OLS estimates. The vertical axis represents the elasticities of explanatory variables.

5. Conclusions and Policy Implications

Based on the panel data of 30 provinces in China from 1997 to 2015, this paper extends the STIRPAT model and uses the quantile regression panel model to empirically study the main influencing factors of CO_2 emissions in China's construction industry, focusing on the different effects of influencing factors in different quantiles. The results show that: (1) Population size, economic growth, energy structure and industrial scale have positive impacts on carbon emissions of construction industry, while technological level has negative impacts. (2) The impact of population size on CO_2 emissions from construction industry in 50th-75th quantile provinces is larger than those in other percentile provinces, which may be related to the different population growth rates in different regions. The impact of economic growth on provinces in 10th-25th quantile is greater than those of provinces in other quantile, which may be caused by the difference of fixed-asset investment in construction industry in different provinces. The difference in patented technology, R&D expenditure and R&D personnel cause energy efficiency has less inhibition on CO_2 emissions of construction industry in the upper 90th quantiles provinces than those of provinces in other quantile. Energy structure has stronger impact on CO_2 emissions of provinces in the 25th-50th and 50th-75th quantiles than other percentile provinces may owe to obvious differences in coal consumption. The effects of industrial scale on CO_2 emissions of provinces in the upper 90th quantile are higher than those of provinces in other quantile because of the differences in scale of construction industry. Therefore, all levels governments and relevant enterprises should pay more attention to the heterogeneous effects of these factors on the construction industry CO_2 emissions in different quantile provinces. People-oriented, tailored to local conditions, different energy saving and emission reduction schemes should be adopted according to the characteristics and problems of different regions, rather than "one-size-fits-all".

The above research conclusions imply the following policy suggestions: (1) The 10th-25th quantile provinces need to further optimize their economic structure and reduce excessive dependence on fixed-assets investment. Local governments should establish special governance mechanism to guide and encourage social capital to develop new energy high-tech industry. (2) For the 25th-50th and 50th-75th quantile provinces of CO_2 emissions in construction industry, the local governments should encourage residents adopt green material in the decoration process and expand the construction of hydropower and nuclear power stations to reduce coal consumption for power generation during construction. The local construction companies can use energy saving composite materials to replace hollow clay bricks, which can reduce the coal consumption for the production of clay bricks. In addition, the application of 3D printing technology in the construction industry is the future development direction of the local construction industry. (3) The upper 90th quantile provinces need to further improving energy efficiency of construction industry. Firstly, the local government should encourage construction enterprises develop and apply new technologies, new equipment, new materials and new craft for green construction, make reasonable indicators of construction energy consumption. Secondly, the local governments should support the merger and acquisition of large construction enterprises with advantages, and accelerate the construction industry to use energy-saving, efficient and environment friendly construction equipments and tools in line with national and industrial standards. Thirdly, local governments should increase investment in R&D funds and encourage scientific research institutions to train technical personnel related with building energy saving and adopt flexible and effective policies to attract relevant professionals.

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