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Original Research

Which Influencing Factors Cause CO_2 Emissions Differences in China's Provincial Construction Industry: Empirical Analysis from a Quantile Regression Model

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Abstract

China is currently the largest emitter in the world. Moreover, the construction industry is the biggest contributor to CO_2 emissions. Most scholars use the averaging method to explore CO_2 emissions driving factors. However, the actual socio-economic variables distribution isn't often normal, with the tail having hidden important information. Based on panel data from 2004-2016, this paper investigates the driving forces of CO_2 emissions through the quantile regression approach. The empirical results show that the impacts of economic growth on CO_2 emissions in the 10^{th}-25^{th}, 50^{th}-75^{th} and 75^{th}-90^{th} quantile provinces are higher than those in the other quantile provinces. The influences of urbanization on CO_2 emissions in the upper 90th are strongest in all the quantile provinces. The affects of construction development on CO_2 emission in the 25^{th}-50^{th} and upper 90^{th} quantile provinces is greater than those in the other quantile provinces, while the effects of energy intensity on CO_2 in the lower 10^{th} and 10^{th}-25^{th} quantile provinces are lower than those in other quantile provinces due to the difference. Consequently, emission reduction departments should take into account the differences of carbon emissions driving forces in different provinces and reasonably formulate policies in mitigating carbon emission.

Keywords: construction industry, carbon emissions, quantile regression approach

Introduction

Massive demand for energy caused by economic growth has led to a substantial increase in carbon dioxide emissions. The International Energy Agency (IEA) announced that global carbon dioxide emissions reached 325 billion tons in 2017. Accumulated global carbon dioxide emissions have brought about a series of environmental problems, such as global warming and the frequent emergence of extreme weather [1]. Owing to huge industrial scale and long-term extensive economic growth, China has become the largest carbon

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emitting country in the world [2]. With reference to the data in the China Statistical Yearbook, energy consumption in China was about 4.30 billion standard coal equivalent (tce) in 2017, accounting for about 23.2% of world energy consumption. To respond to the climate crisis caused by the large amount of greenhouse gas (GHG), our government proposed to reach peak carbon dioxide emissions by 2030 and increase the share of non-fossil energy consumption to about 20% [3]. However, China remains in the process of industrialization and urbanization for a long time [4], and continues to require a large amount of energy. Thus, server carbon reduction task is a difficult challenge faced by the Chinese government.

It is generally recognized that the construction sector is one of the main sources of economic growth and energy consumption either in China, or other countries in the world [5]. The IPCC's fifth assessment report showed that construction terminal product accounted for 32% of global energy consumption. The construction sector has become an important industry in China's economy and an important force for stimulating economic growth. Simultaneously, the construction industry in China, an energy-intensive and high-emission industry, consumes a large number of building materials: about 70% of cement products and 25% of steel products [6]. The energy consumption relevant to the construction industry increased from 13.345 million tons of standard coal equivalent (tce) increased to 79.91 million thousand tons of standard coal equivalent from 1995-2016, which averaged growth rate of up to 22.7%. Therefore, the construction sector has not only contributed substantially to China's economic growth, but also resulted in environmental degradation [7]. According to data in the China Statistical Yearbook, CO_2 emissions from the construction industry contributed to about 27.9~34.3% of the total CO_2 emissions during the period of 1995-2016. Consequently, it is urgent to investigate the main driving forces of CO_2 emissions in the construction sector for protecting the environment and mitigating China's total emissions.

At present, the unbalanced China's construction industry development leads to huge differences in CO_2 emissions characteristics and emission reduction policies among China's provinces [8,9]. Fig. 1 shows the energy and CO_2 emissions statistics of China's 30 provinces in 2016. GuangXi province has the lowest energy consumption at only 0.35 million tonnes of standard coal. In contrast, Shandong province has the highest energy consumption at 9.7 million tonnes of standard coal, which is more than twenty-eight times the energy consumption of Guangxi. Jiangsu has the lowest energy intensity at about 0.02 tonne/ten thousand yuan, and Neimenggu has the highest energy intensity at about 2.19 tonne/ten thousand yuan, which is more than ten times the former. The difference in total energy consumption and energy intensity are the major cause of the difference in CO_2 emissions [10]. According to our calculation, in 2016, the highest energy-related CO_2 emissions are recorded in Zhejiang province, emitting about 310.03 million tonnes. This is nearly 28 times the emissions of Hainan province at only 3.84 million tonnes CO_2. Thus, it is necessary to conduct thorough study on the spatial differences of carbon emissions in China's construction industry.

The construction industry is a resource-intensive industry with high-energy consumption and heavy-emissions, attracting numerous scholars to quantify the driving factors affecting CO_2 emissions from construction sector. There are two kinds of CO_2 emissions in the construction industry: direct and indirect CO_2 emissions [11]. The direct CO_2 emissions are the CO_2 emissions caused by energy consumption [12]. The indirect CO_2 emissions, accounted for a large

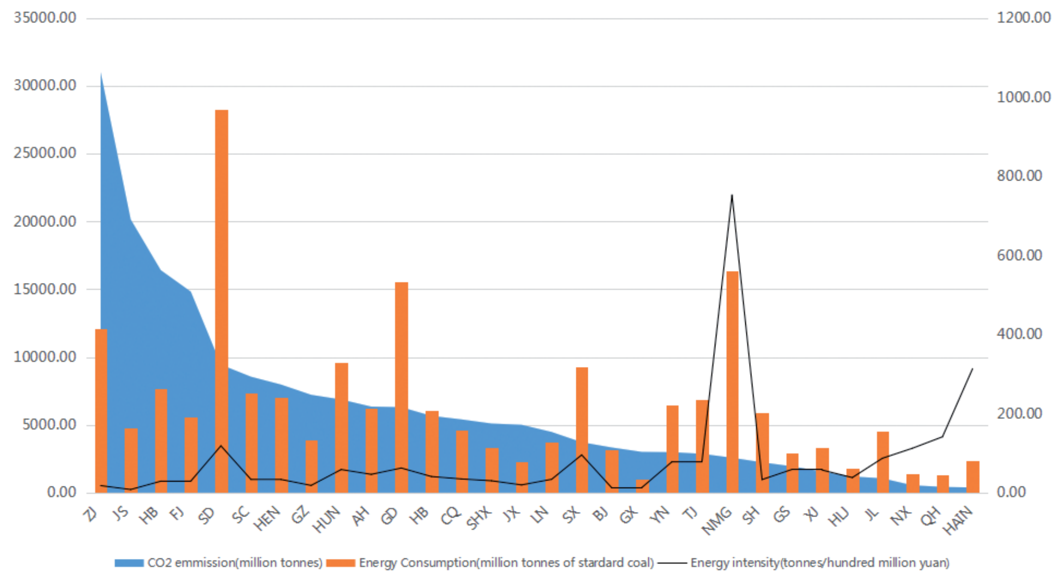

Fig. 1. Energy and CO_2 emissions in China's 30 provinces in 2016.

proportion of total CO_2 emissions in the construction industry, refer to those occurred in the upstream activities [13], such as the production of brick and cement.

At present, most research is based on decomposition methods, including index decomposition analysis (IDA) and structural decomposition analysis (SDA) – two popular methods. Chen and Shi et al. applied the SDA to reveal the drivers contributing to the carbon emissions difference in the context of construction industry between USA and China [14]. The results demonstrated that the total final demand effect contributed most to narrowing the emissions difference, while the final demand ratio effect had the largest enlarging impact on the difference. Hong et al. applied SDA to quantify the effects of driving factors and declared that the energy consumption trajectory of China's construction industry is the result of competition between the effect of increasing final demand and improvement in energy efficiency [15]. Moreover, it is appreciated that most studies prefer to adopt the logarithmic mean divisia index (LMDI) [16], one kind of the IDA, to analyze the driving factors of carbon emissions, which can be formulated more flexibly and requires less data than the SDA [17]. Lin and Liu adopted the LMDI model to survey the changes of CO_2 emissions from China's building construction industry during 1991-2010 into five driving factors [18], namely emission-factor effect, structure effect, intensity effect, profit effect, and activity effect. The results found that CO_2 emissions were closely related to electricity consumption. Lu et al. employed the LMDI method to identify the longitudinal impact of seven key driving factors [19] involved in energy intensity, machinery efficiency, energy structure, building material consumption, automation level by area, unit cost, and a summary of emission influences on construction carbon emissions in China from 1994 to 2012. The results suggest that the consumption of building materials was the largest contributor to the total increase of carbon emissions. Using the LMDI method, Li and Cai et al. calculated the contributions of energy structure, energy intensity, industrial structure, land economic output, population density, and area of construction land area to carbon emissions from the construction land in Shanghai [20], and confirmed land economic output as being the main driving factor. Ma and Cai et al. [21] employed the LMDI to decompose five driving forces from the Kaya identity to assess carbon mitigation in Chinese commercial building values in 2001-2015. The results indicated that only the reciprocal of GDP per capita of tertiary industry in China and the intensity two driving forces contributed negatively. Jiang et al. [22], Li et al. [23], and Lu et al. [24] also applied the LMDI method to examine the driving factors on carbon emissions from the construction sector.

Summarizing the previous literature, we find that although much important research has been carried out to investigate the driving factor of carbon emissions in the construction sector, some omissions still exist. Firstly, most existing studies don't take regional differences into account, resulting in low applicability and practicality. Second, most researchers used the LMDI, SDA to investigate the driving forces of CO_2 emissions, rarely based on econometric models. Third, most scholars use mean regression analysis (i.e., ordinary least squares method) to estimate the impact of the main impact factors of CO_2 emissions based on the assumption that the data of economic variables follows normal distribution. However, the realistic data distribution of socio-economic variables is skewed due to the complexity and variability of socioeconomic phenomena, implying important information. Xu and Lin et al. applied the quantile regression to explore the impact of driving factors in China [25-27]. Compared with the traditional OLS, quantile regression can fully reveal the heterogeneous influence of explanatory variables on the different quantiles in the explained variable.

This paper uses the different quantiles regression to explore the impacts of the driving forces on the CO_2 emissions in the construction sector, with a panel data of China's 30 provinces during the period 2001 to 2016. This paper is composed of five sections, the remaining sections are as follows: Section 2 comprehensively reviews the related literature on CO_2 emissions. Section 3 is related to the econometric model establishment and the data description. At the same time, the abbreviations used in this paper and their explanations are shown as Table 1. Section 4 presents the estimation results. Section 5 implements an in-depth discussion on quantile regression results. Conclusions and policy suggestions are placed in Section 6.

Table 1. The list of abbreviations and their explanations.

Symbol	Description
CO_{2dir} and CO_{2ind}	Direct CO_2 emissions and Indirect CO_2 emissions, respectively
I	The pollution intensity of a pollutant
P	The total population
A	The degree of economic development
T	Energy efficiency
CO_2	Carbon dioxide emissions (10,000 tons)
POP	Total population (10,000 people)
GDP	Economic growth
EI	Energy intensity
URB	Urbanization
ENS	Energy structure
CA	The development level of the construction industry

Table 2. CO_2 emission coefficient of different building materials.

Building materials	Cement	Steel	Glass	Wood	Aluminum
CO_2 emission coefficient (kg/kg)	0.822	1.789	0.966	-824.8	2.6

Experimental

Estimating CO_2

In this paper, estimating CO_2 in the construction industry is divided into two parts: direct and indirect emissions. The direct CO_2 emissions are calculated by the consumption of various fossil fuels (e.g., raw coal, briquette, coke, gasoline, diesel, kerosene, fuel oil, lubricating oil, liquefied petroleum gas, natural gas, heat and electricity) multiplied by their CO_2 emission factors. Indirect carbon dioxide emissions are produced from the consumption of different building materials (e.g., cement, steel, glass, wood and aluminum). Based on the CO_2 emissions coefficients published by IPCC (2006) [28], we establish Eq. (1) to obtain the construction industry's total CO_2 emissions for the 30 provinces:

$$CO_2 = CO_{2dir} + CO_{2ind} = \sum_{i=1}^{10} C_i * \alpha_i * f_i * e_i * \frac{12}{44} + \sum_{j=1}^{5} M_j * \beta_j * (1-\varepsilon_j) \tag{1}$$

…where CO_2 indicates the total CO_2 emissions, CO_{2dir} and CO_{2ind} represent direct CO_2 emissions and indirect CO_2 emissions, respectively, i and j depict the primary fossil energy and building materials, respectively. C_i represents the consumption of different kinds of energy, α_i, f_i and e_i describe low calorific value, carbon content, and carbon oxidation rate of fossil fuel type i, respectively. M_j depicts the usage of various building materials, β_j and ε_j refer to the CO_2 emission coefficient (Table 2) and recovery coefficient of building materials, respectively.

Considering the building materials' recycling, the calculation of CO_2 emissions of recyclable materials should be based on the amount of non-recycled consumption. Among which, the recovery coefficient of steel and aluminum material are 0.8 and 0.85, respectively. In addition, wood is an environment-contributor, absorbing a large amount of CO_2. Consequently, the carbon dioxide emission coefficient of wood is negative. Therefore, the CO_2 emissions from the construction industry calculated by Eq. (1) from 2004 to 2016 for the 30 provinces are shown in Table 3.

Model Specification

Numerous scholars have used the STIRPAT model, a modification of the IPAT model proposed by Dietz and Rosa, to explore the influence of environmental pollution factors. The equation is represented as follows:

$$I_t = aP_t^b A_t^c T_t^d e_t \tag{2}$$

…where *a* represents the intercept term, *I* indicates the pollution intensity of a pollutant; *P* represents the total population; *A* depicts the prosperity of economics in a country; *T* is the level of technological development; *b*, *c* and *d* are the coefficients of environmental effects with correspond to *P*, *A*, and *T*; *t* means the year; and et expresses the random error term. Consistent with the environmental Kuznets curve, the hypothesis, the links between economic progress and pollutant emissions generally appears an inverted "U-shape" situation [29]. In contrast, technological progress is conducive to reducing the emission of environmental pollutants.

Considering the logarithm of the variables is a simple and effective approach, all variables in this study are logarithmically processed in order to eliminate possible heteroscedasticity. Thus, Eq. (2) becomes the following form:

$$lnI_{it} = lna + b(lnP_{it}) + c(lnA_{it}) + d(lnT_{it}) + e_{it} \tag{3}$$

…where *P* represents total population, *A* is the degree of economic development, and *T* indicates energy efficiency and is calculated by dividing energy use by gross domestic product. Hence, Eq. (3) can be changed as:

$$\ln CO_{2it} = lna + b(\ln POP_{it}) + c(\ln GDP_{it}) + d(\ln EI_{it}) + e_{it} \tag{4}$$

…where CO_2 means carbon dioxide emissions (10,000 tons), POP is total population (10,000 people), GDP indicates economic growth and is represented by GDP per capita, and *EI* represents energy intensity and is calculated as energy consumption divided by GDP (tce per 10,000 yuan). Many studies suggest that *EI* represents the impact of technological progress on carbon dioxide emissions [30], and a and e are the intercept and interference terms, respectively.

In order to comprehensively and accurately explore the main motivating factors of carbon dioxide emissions in the construction sector, we added several other important factors to the STIRPAT model according to China's authentic situation. First of all, China is currently at the stage of rapid urbanization. The China Statistical Yearbook shows that the urbanization rate has increased from 26% in 1990 to 57% in 2016 in China. Urbanization does not only lead to rapid expansion of urban population, but also results in the significant demand of residence. On the one hand, increasing urban population will require lots of energy (e.g., electricity,

Table 3. The CO_2 Emissions from Construction Industry in 30 provinces during the period of 2004-2016.

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
Hainan	86.12	89.98	102.40	117.49	175.13	224.37	232.68	385.38	452.11	559.27	426.30	337.25	383.90	274.80
Qinghai	153.07	134.03	132.70	205.85	308.27	411.65	587.48	350.53	378.70	400.81	428.65	401.19	424.29	332.09
Ningxia	206.19	218.07	249.45	271.85	357.91	409.01	514.87	617.66	577.28	777.26	836.32	551.24	546.11	471.79
Gansu	660.54	689.19	825.66	632.05	1304.04	934.35	943.55	2002.03	1403.59	1995.59	2163.93	1552.95	1941.47	1311.46
Guizhou	664.42	565.76	654.01	736.85	810.44	1189.88	851.15	1253.55	1460.73	2594.53	3164.19	3917.85	7216.00	1929.18
Yunnan	840.54	1026.96	1370.03	1285.37	1500.43	1732.87	2354.42	2115.86	2566.62	5534.77	6156.32	2873.59	2987.39	2488.09
Tianjin	852.79	763.44	955.57	1371.56	1503.60	2043.39	1854.71	2798.66	2750.93	3677.58	4956.48	3238.85	2866.03	2279.51
Heilongjiang	857.17	673.43	731.53	840.91	1020.01	1112.85	1380.11	1672.29	1522.26	1558.80	1626.99	1265.67	1194.10	1188.93
Guangxi	902.20	904.50	978.16	982.62	1071.65	1398.24	1673.87	1905.69	2415.04	1989.62	2095.03	1287.21	3006.54	1585.41
Neimenggu	909.23	986.94	867.99	1146.74	2532.07	1711.12	2002.90	2141.87	1888.95	1705.43	1677.46	1748.56	2575.64	1684.22
Jiangxi	941.26	1103.55	1316.43	1229.33	1422.62	1679.52	1908.23	3025.77	3026.02	3989.64	2011.18	5137.27	5005.49	2445.87
Shaanxi	942.06	1333.10	1418.11	1872.89	3114.73	3258.96	3526.45	6049.83	4000.27	4328.54	4912.18	4742.68	5098.83	3430.66
FuJian	968.44	1776.79	2466.29	2032.52	3778.26	4664.54	5858.51	5826.78	7284.62	9741.96	12757.4	12815.4	14819.2	6522.36
Xinjiang	1013.36	540.28	1008.18	730.71	836.42	862.13	1063.77	3262.21	1780.50	1691.50	2299.25	1735.18	1554.75	1413.71
shanxi	1315.89	1647.46	1549.58	1888.52	2915.97	2950.45	4461.78	3127.72	3178.99	3274.69	3987.01	3338.43	3718.40	2873.45
Anhui	1503.80	1572.96	1842.19	2364.30	2599.59	3009.61	4117.30	4443.25	4444.62	5576.37	5984.31	5056.12	6345.99	3758.49
Chongqing	1538.74	1584.49	1658.15	2029.90	2563.58	2577.44	4695.74	4655.03	4277.93	5131.60	5354.47	5177.46	5401.90	3588.19
Beijing	1583.10	1686.50	1669.70	2022.09	2305.51	3289.57	3859.29	3949.49	3178.94	3589.36	3665.32	3560.05	3331.50	2899.26
Jilin	1719.55	439.17	880.04	889.01	1186.10	1537.54	1554.90	1724.86	95278.7	6676.63	7101.71	2064.35	1056.63	9393.01
Shanghai	1752.82	2121.89	2032.52	2041.72	2140.34	2290.75	2432.53	2549.42	2335.44	2923.80	2505.19	2131.53	2237.35	2268.87
Henan	1808.00	1860.75	2636.23	3863.51	4384.68	5397.40	6732.65	6897.43	8434.85	8021.29	21483.0	5947.70	7969.94	6572.11
Hubei	2088.66	2719.45	5099.94	2674.47	3910.42	4078.21	11026.2	49915.3	47795.8	17722.6	7426.52	7952.04	5664.54	12928.8
Liaoning	2117.80	2017.52	2288.18	2604.82	3508.06	4796.99	6105.24	9916.94	7946.17	14861.3	14392.7	4871.69	4475.01	6146.34
Hebei	2325.32	3185.85	3197.96	3673.85	3229.36	3822.59	3958.30	8377.36	15105.2	13761.8	16234.8	13181.1	16405.6	8189.16
Sichuan	2491.17	2632.43	3024.73	3466.34	3974.43	4954.12	10370.7	12586.2	18545.6	19604.9	21712.5	8920.25	8549.53	9294.83
Guangdong	2917.51	3532.14	3742.07	3773.16	3661.12	4105.98	5215.77	8195.46	2047.62	6962.28	7433.48	6469.25	6303.15	4950.69
Shangdong	3169.88	3825.65	4369.59	3503.23	5561.04	6925.71	7735.13	7631.88	19086.9	10637.9	10706.3	10201.4	9434.86	7906.89
Hunan	4726.68	2896.48	3579.02	3829.31	4226.44	5092.97	5552.99	5198.83	6044.29	6623.02	7050.13	7201.66	6869.29	5299.31
Jiangsu	6542.72	7211.83	8070.76	10301.9	13248.9	13580.5	15639.6	64076.9	27636.2	21737.7	23056.4	20847.0	20145.5	19392.0
Zhejiang	9336.87	11416.5	13412.6	13852.1	17011.9	17990.2	20701.4	25303.8	27043.7	30552.3	31417.2	30680.2	31003.3	21517.1
QuanGuo	56248.3	60201.9	71479.4	75391.1	94986.7	106672	136992	249454	291040	214617	231959	175957	182075	149775

Notes: Lines 2nd to 31st are CO_2 emissions from construction industry in China from 2004 to 2016 in Table 3, while lines 32nd is CO_2 emissions from the construction industry as a whole in China.

coal and natural gas) in the course of life and work, on the other hand, magnanimous residential buildings have tremendous demand for building materials. The Ministry of Housing and Construction of China forecasts that 15-20 billion square meters of new buildings will need to be constructed for the sake of providing housing for the populatoin migrating to the city in 2005-2020 [31]. Thus, urbanization is taken into accounted in the model in order to examine its impact on CO_2 emissions in the construction sector. In addition, numerous new buildings will require the consumption of a lot of fossil energy and building materials, inevitably producing a large amount of carbon dioxide and accelerating the construction industry improvement. Consequently, the development level of the construction industry has been brought into the framework of this analysis. Finally, China's construction industry has several deficiencies, such as high consumption, high pollution and low efficiency, which are mainly due to the large consumption of high-polluting coal. The annual average rate of coal consumption accounted for 62.3% during 1980-2015. Excessive use of coal is the greatest contributor to massive carbon dioxide and has a negative impact on the environment. The proportion of coal consumption (i.e., energy structure) is therefore included in the econometric model. Based on the STIRPAT model and the above analysis, the econometric model of CO_2 emissions in China's construction sector is established as follows:

$$lnCO_{2it} = lna + \beta_1(lnPOP_{it}) + \beta_2(lnGDP_{it}) + \beta_3(lnEI_{it}) + \beta_4(LnURB_{it}) + \beta_5(LnENS_{it}) + \beta_6(lnCA_{it}) + \varepsilon_{it} \tag{5}$$

…where CO_2, POP, GDP and EI are the same as in Eq. (5), URB is urbanization and is calculated by dividing the urban population by the total population, and ENS denotes energy structure and is calculated by dividing coal consumption in the construction industry by its total energy consumption. CA indicates the development level of the construction industry and is calculated by construction added value divided by GDP.

Quantile Regression Model

The quantile regression model was first proposed by Koenker and Bassett. The model compensates for the shortcomings of the OLS method, relaxes the random error term homoscedasticity assumptions, and allows for the existence of unobserved individual heterogeneity and heteroscedasticity in the data. Based on the different quantile points, the method makes full use of the sample data to perform regression analysis, and obtains all the quantile regression models between the conditional quantiles of the explained variable and the explanatory variables. Therefore, this method can more accurately and completely describe the effect of the interpreted variable on the interpreted variable at different specific points. Moreover, the quantile regression's parameter estimate is more robust than that in the OLS regression. Therefore, we use the quantile regression method to explore the impact of different driving forces along the actual distribution of the construction sector's CO_2 emissions in different provinces. The mathematical formula of the quantile regression model based on the panel data is as follows:

$$y_i = x_i^{'}\beta_\theta + \mu\theta_{i,} 0 < \theta < 1 \tag{6}$$

$$Quant_\theta(y_i \mid x_i) = x_i\beta_\theta \tag{7}$$

…where x represents the vector of the explanatory variables, y denotes the explained variable, β is the coefficient vector, and μ indicates random error term (whose conditional quantile distribution is equal to zero). $Quant_\theta(y_i|x_i)$ is the θ^{th} quantile of the explained variable. β_θ indicates the θ^{th} quantile regression estimator, and is the solution of the following formula:

$$\min \sum_{y_i \geq x_i^{'}\beta} \theta \left| y_i - x_i^{'}\beta \right| + \sum_{y_i < x_i^{'}\beta} (1-\theta) y_i - x_i^{'}\beta \tag{8}$$

This above equation will obtain different parameter estimates with different quantiles distribution. In order to effectively investigate the impact of explanatory variables on interpreted variables under different distribution situations, we set up the 10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th} quantile regressions, respectively. In this study, we use the bootstrap method proposed by Buchinsky to estimate the confidence interval of quantile regression coefficients. Different from the traditional piecewise regression model, the quantile regression model observed all sample values to estimate the parameters and fit different quantiles, especially when the error term has heteroskedasticity and is not a normal distribution. In order to investigate the complication impact of the influencing factors on different quantiles in the dependent variables, we transform Equation (5) as follows:

$$Q_\tau l\,n\,CO_{2it} = (\mathrm{l})na_\tau + \beta_{1\tau}(\ln POP_{it}) + \beta_{2\tau}(\ln GDP_{it}) + \beta_{3\tau}(\ln EI_{it}) + \beta_{4\tau}(\ln URB_{it}) + \beta_{5\tau}(\ln E\mathrm{NS}_{it}) + \beta_{6\tau}(\ln \mathrm{CA}_{it}) + \varepsilon_{it} \tag{9}$$

…where Q_t and $(\mathrm{lna})_\tau$ represent the regression parameter of τ^{th} quantile in the dependent variable and constant term, respectively. $\beta_{1\tau}$, $\beta_{2\tau}$, $\beta_{3\tau}$, $\beta_{4\tau}$, $\beta_{5\tau}$ indicate the regression parameters of τth quantile in the explanatory variables.

Results

Summary Statistics

The definitions and statistical descriptions of the explanatory and dependent variables in this study are

Table 4. The summary statistical of all the variables in the study.

Variable	Definition	Units of measurement	Mean	Std. dev	Min	Max
CO_2	Carbon dioxide emissions	10,000 tons	5144.6	8384.9	86.1	95278.7
POP	Total population	10,000 people	4427.1	2659.1	539	10999
GDP	GDP per capita	Yuan	16383.2	8452.5	6644.9	44040.9
URB	Urbanization level	Percent	0.512	0.145	0.164	0.896
ENS	Energy structure	Percent	0.578	0.167	0.062	0.991
EI	Energy intensity	Tce per 10^4 yuan	0.074	0.061	0.006	0.494
CA	Construction development	Percent	0.118	0.083	0.014	0.780

shown in Table 4. Before the regression analysis, we describe the holistic change trend of all variables during the 2004 to 2016 period. As shown in Fig. 2, the CO_2 emission in China's construction industry rapidly rose from 0.56 billion tons in 2004 to 2.91 billion tons in 2012, with average annual growth rate of 13%. Since 2012, CO_2 emissions have begun to show a downward trend in China's construction industry owing to the government's emphasis on carbon reduction. Firstly, population size: since relaxing the two-children policy in 2016, population growth has to some extent rebounded. Secondly, urbanization level: the urbanization rate increased from 41.8% in 2004 to 57.3% in 2016. Thirdly, economic growth: with an increasing trend, GDP per capita increased from 12,418 yuan in 2004 to 18,055 yuan in 2015. Fourthly, construction development. Real estate construction has made the gross output improve continuously in the construction industry. Fifthly, energy structure: in the period of 2004-2016, coal consumption accounted for 63.2% of total energy consumption in the construction industry. Finally, energy intensity. With the advanced energy-saving technologies, energy consumption gradually declined from 0.073 tce per 10,000 yuan output in 2006 to 0.067 tce per 10,000 yuan output in 2016.

The vast land and natural resources have led to the differentiation of regional resources endowment and development level, which has also caused significant regional differences in CO_2 emissions across China. So, what are the aggregation characteristics of carbon dioxide emissions in spatial distribution? Besides, in terms of Tobler's first law, there is a general connection between any spatial unit, which means that spatial data can interact because of their geographical location. On the basis of the above assumptions, we preliminarily analyzed the quantile distribution of CO_2 emissions from the construction industry in China. To make a thorough inquiry for the distribution characteristics in CO_2 emissions at the provincial level, we divide the 30 provinces into four groups by using the quartile distribution method in light of the construction sector's CO_2 emissions in 2004 (Fig. 3a), in 2008 (Fig. 3b), in 2012 (Fig. 3c) and in 2016 (Fig. 3d). During the period of 2004-2016, CO_2 emissions are increasing year by year in various provinces' construction sectors. In 2000, four provinces ranked in the highest carbon emissions range. However, by 2012, ten provinces were ranked in the highest emissions range. The number of carbon emissions in the first grade increased significantly. By 2016, the number of the highest level provinces has declined. Moreover, Zhejiang and Jiangsu provinces retained their positions in the highest CO_2 emissions group. This is because Zhejiang and Jiangsu provinces have been at the forefront of the whole country. The changes in the numbers of provinces in the 2^{nd} and 3rd groups are not obvious. However, the number of provinces in the 4th groups decreased sharply. In 2000, twelve provinces divided into the lowest carbon emissions range. Nevertheless, by 2012, only five provinces were ranked in the lowest emissions range. Merely Hainan, Qinghai, Ningxia and Heilongjiang provinces have maintained their respective status in the lowest CO_2 emissions group. In a word, the construction industry's CO_2 emissions are evident distinctions in in the different provinces.

Multicollinearity Test

Generally speaking, the explanatory variables may be completely collinear or approximately multicollinearity, producing some adverse consequences. In the case of complete multicollinearity, the estimation of parameters does not exist, or the significance tests of variables are ineffective. Therefore, before estimating model regression, we urgently need to conduct an examination of the issue of multicollinearity in the econometric model. This paper applies Klein to realize the multicollinearity test. The concrete steps of multicollinearity test are as follows: (1) We compute the correlation coefficient between the explanatory variables in this model and acquire the correlation coefficient matrix. (2) On account of the fixed effect panel model, this paper performed a regression estimation and got the determination coefficient (R^2 = 0.9131). As shown in Table 5, it is apparent that all correlation coefficients' absolute values are significantly less than R^2, suggesting that multiple collinearity between explanatory variables can be omitted.

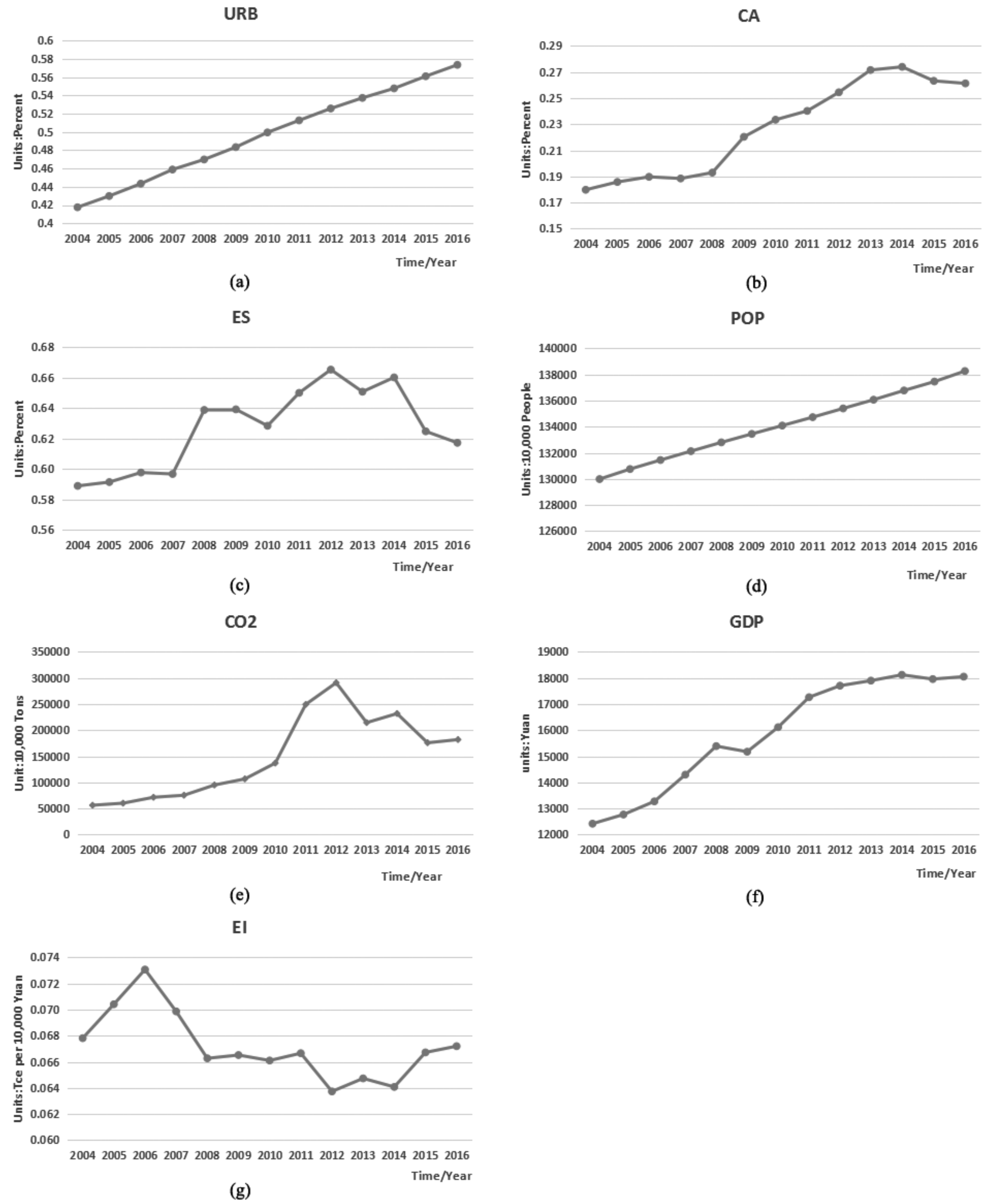

Fig. 2. The trends of the CO_2 emission, population size, urbanization level, per capita GDP, energy intensity, construction development, energy structure in the construction sector during the period of 2004-2016.

Unit Root Test

The complicated and changeable economic phenomenon makes the sequences of numerous economic variables non-stationary. If the non-stationary sequences are not transformed into steady sequence before operating regression estimation, the estimation result will deviate from the actual economic situations. For the sake of precisely telling the stationariness of these variable sequences, we use three extensive test measures (Fisher-ADF, Fisher-PP and IPS) to implement panel unit root tests. Table 6 intuitively provides the stationarity test results for the explanatory variables and explained variables. It can be seen that the results of the ADF, PP and IPS tests are basically maintenance consistent. The result suggests that the level variable sequences are nonstationary, but their first-order difference sequences are stationary.

Test of Normal Distribution

The normal distribution of sample data strongly affects the robustness of regression estimation results. Therefore, before regression estimation analysis, we

Table 5. The correlation coefficient matrix.

	LnPOP	LnURB	LnGDP	LnCA	LnES	LnEI
LnPOP	1.0000					
LnURB	0.7179	1.0000				
LnGDP	0.2898	-0.1558	1.0000			
LnCA	0.3176	-0.0543	0.7635	1.0000		
LnES	0.0552	0.0491	-0.2184	0.1989	1.0000	
LnEI	-0.0067	0.2393	-0.3122	-0.2605	-0.0362	1.0000

conducted a normality test for all variables ($LnCO_2$, LnPOP, LnURB, LnGDP, LnEI, LnENS, LnCA), including graphic and numerical two methods.

In this paper, we carry out statistical tests for all logarithmic variables. As shown in Table 7, the results indicate that all the variables are not normally distributed. (1) Skewness is used to measure the symmetry of data distribution. Only if the skewness coefficient is equal to 0, which demonstrates the data distribution is the same as of normal distribution. From Table 7, it can clearly perform all variables skewness coefficients that are not equal to zero. (2) Kurtosis is the measurement of dispersion of sample data. Only when kurtosis is equal to 3 can data distribution be considered normal. The results declare that the kurtosis coefficients of all variables are not equal to 3, suggesting that the distributions of all variables are not normal. (3) The Shapiro-Wilk is commonly applied into small sample normal distribution tests. The probability p values are less than the 5% significance level in the Shapiro-Wilk test, which demonstrates that all the variables do not follow normal distribution.

This paper also adopts the graphical method to intuitively display the variables distribution. We employ the Q-Q test plot to implement a normality test. Fig. 4 indicates that the observed values of all variables deviate from the red line. This result declares these variables are not normally distributed, and the degree of deviation has increased gradually in recent years.

Quantile Regression Results

Not only can each quantile roundly describe the distinct distribution characteristics for CO_2 emissions, but also different quantile equations can directly promulgate the marginal effects of variables on CO_2 emissions. In this paper, five representative quantiles (i.e., 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th}) are chosen to implement quantile regression. As shown in Table 8, in light of the annual average CO_2 emissions from different region construction industries, we separate the 30 provinces into six groups. Table 9 provides the estimation results of the quantile regression of CO_2 emissions from the construction industry. To facilitate comparative analysis, the data OLS regression results are listed in the last column of Table 9. It can be seen that all the independent variables were significantly tested at 10% or higher by significance test.

Table 9 shows that quantile regression can give a comprehensive impact coefficient of each factor on CO_2 emissions in different quantiles. Specifically, the impact coefficients of population size on CO_2 emissions in the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} quantiles are 1.1372, 1.1252, 1.2006, 1.3109, 1.3915, respectively. Obviously, the influence coefficient in the 75^{th} and 90^{th} quantiles was the greatest. However, the OLS estimated value is 2.2472, which is higher than those in all quantiles. By comparison, other variables have similar situations. Consequently, quantile regression can bring to light the integrated effects of driving factors on CO_2 emissions in different quantiles. While OLS estimation can only provide the average effect. In a word, it is feasible and reasonable to explore the diverse effect of driving force on CO_2 emissions by quantile regression model.

Discussion

The differences in the influencing factors affecting CO_2 emissions deserve further exploration. Some extrusive issues in quantile regression are discussed as follows.

1) The impacts of economic growth on CO_2 emissions in the 10^{th}-25^{th}, 50th-75th and 75^{th}-90^{th} quantile provinces are higher than those in the other quantile provinces.

The results show that there are significant discriminations in the effect of economic growth in different quantile provinces. This is mainly attributable to fixed asset investment activities – one of the important sources of China's economic growth [32]. Fixed assets investment activities cover the construction of roads, housing and other buildings, rapidly promoting construction industry development and requiring plenty of building materials. However, the building materials industry is energy-intensive and high-emission industries consume a lot of coal and result in discharging massive CO_2 [33]. During the period of 2004-2016, the average annual fixed assets investment in the 10^{th}-25^{th}, 50^{th}-75^{th} and 75^{th}-90^{th} quantile provinces were 15.57, 9.63 and 12.74 (billion yuan), respectively, which were much higher than those in the lower 10^{th}

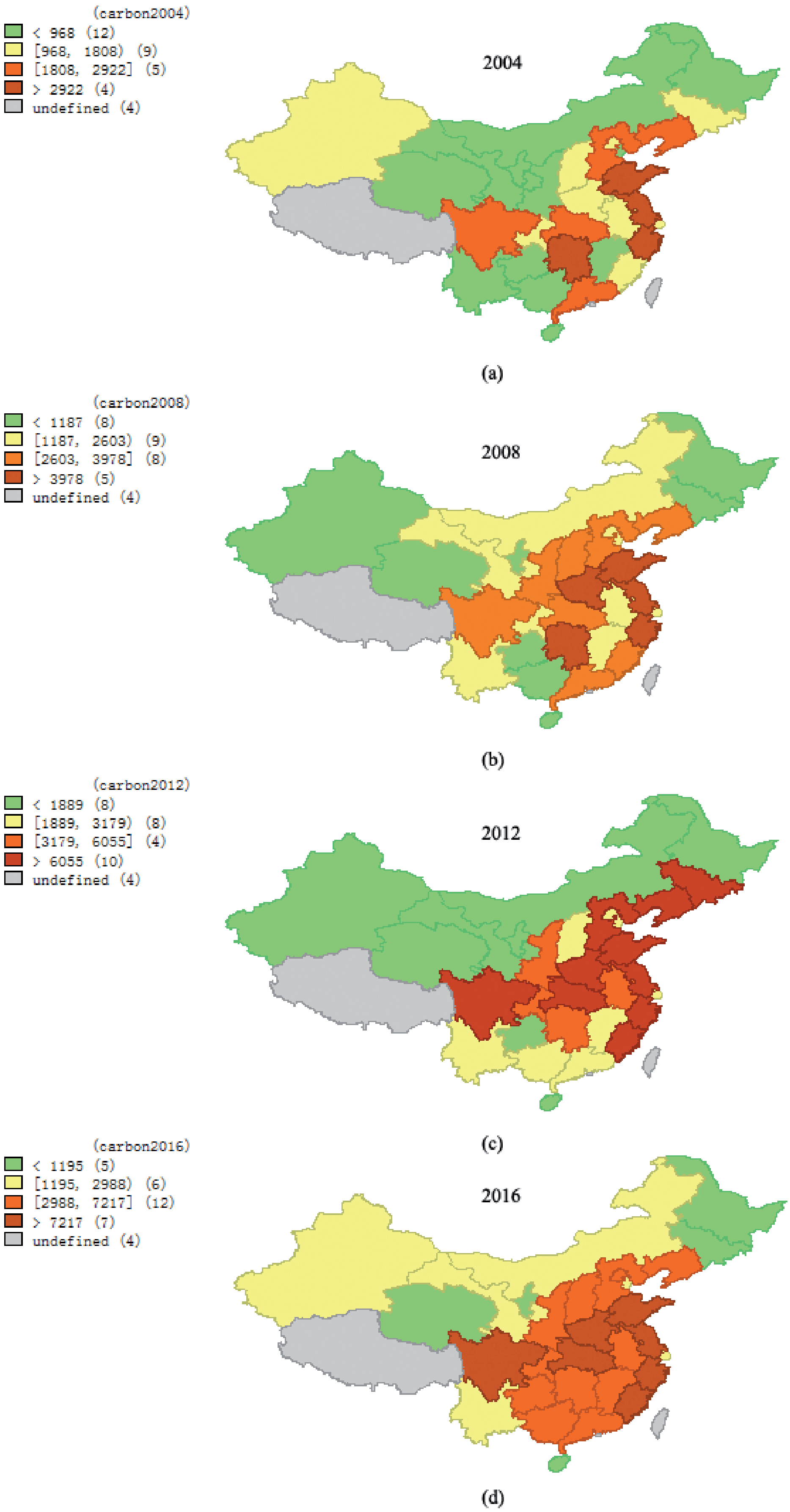

Fig. 3. Provincial distribution of CO_2 emissions in China's construction industry (Unit: 10,000 tons). a) , b), c), d) indicates Provincial distribution of CO_2 emissions in 2004, 2008, 2012, 2016, respectively.

Table 6. Results of panel unit root tests.

	Series	Fisher ADF		Fisher PP		IPS	
		Constant	Trend and intercept	Constant	Trendand intercept	Constant	Trend and intercept
Levels	CO_2	48.57	90.398**	47.589	115.534**	1.62	-1.818**
	POP	103.8***	74.599*	107.2**	79.358**	-0.12**	2.568
	URB	174.94*	302.579	195.31	358.738	-10.4**	-59.326
	GDP	73.65*	15.863	115.4**	26.028	-2.08**	7.280
	CA	147.79*	106.557	244.3**	178.66	-5.86	-3.626
	ES	83.08**	79.07*	97.20	121.711	-1.91**	-1.794*
	EI	116.91**	107.912	160.06	188.836	-4.26*	-3.058
First difference	CO_2	257.2***	178.860***	353.1***	327.538***	-13.5***	-8.761***
	POP	135.40***	138.358***	162.9***	210.554***	-5.0***	-5.467***
	URB	363.7***	301.301***	435.3***	406.817***	-65.5***	-53.963***
	GDP	124.3***	124.514***	134.1***	233.156***	-5.5***	-5.501***
	CA	174.2***	141.885***	202.2***	186.949***	-8.7***	-6.623***
	ES	207.2***	143.844***	291.5***	270.706***	-10.7***	-6.361***
	EI	259.8***	211.5***	330.2***	341.716***	-13.8***	-11.177***

Note: The optimal lag is chosen according to AKAIKE information criterion (AIC) and Schwartz information criterion (SC).

quantile provinces (2.95 billion yuan), 25^{th}-50^{th} quantile provinces (2.04 billion yuan), upper 90^{th} quantile provinces (4.21 billion yuan). Due to the policy of "one belt and one way", Xinjiang and Gansu provinces have significantly increased investment in fixed assets, resulting in a significant increase in carbon emissions. Therefore, the influences of economic growth on CO_2 emissions in the 10^{th}-25^{th}, 50^{th}-75^{th} and 75^{th}-90^{th} quantile provinces are stronger than in other quantile provinces.

2) The influences of urbanization on CO_2 emissions in the upper 90^{th} are stronger than those in other quantile provinces.

This can be interpreted as the entire difference between housing demand and real estate investment. With comfortable living environment and sound infrastructure, urban areas attract a large number of rural residents migrating to urban areas, resulting in a significant increase in demand for ousting and rapid development of urban real estate [34]. Besides, the heterogeneity of urbanization level has caused different growth rates of the real estate industry. The prosperity of the real estate industry is bound to require more energy-intensive building materials such as steel and cement, producing substantial CO_2. During the 2004-2016 period, the annual average real estate investment in the upper 90^{th} quantile provinces was 438.9 billion yuan – far larger than those in the 75^{th}-90^{th} quantile provinces (311.6), 50^{th}-75^{th} quantile provinces (295.5), 25^{th}-50^{th} quantile provinces (186.1), 10^{th}-25^{th} quantile provinces (100.7) and lower 10^{th} quantile provinces (45.5). Moreover, the superior environments in Jiangsu and Zhejiang have attracted massive talent,

Table 7. Res Tests of normal distribution.

Variable	Skewness	Kurtosis	Shapiro-Wilk test		Obs.
			Statistics	Sig.	
$LnCO_2$	-0.107	3.339	0.995	0.181	390
LnPOP	-0.828	3.192	0.928	0.000	390
LnURB	-0.108	3.627	0.983	0.000	390
LnGDP	0.659	2.763	0.949	0.000	390
LnCA	0.104	4.557	0.980	0.000	390
LnES	-1.763	8.836	0.884	0.000	390
LnEI	-0.017	2.771	0.997	0.008	390

Table 8. Provincial distribution in term of total CO_2 emissions in the construction sector.

Quantile	Province
The lower 10th quantile group	Hainan Qinghai Ningxia
The 10th-25th quantile group	Heilongjiang Gansu Xinjiang Guangxi Neimenggu
The 25th-50th quantile group	Guizhou Shanghai Tianjin Jiangxi Yunnan shanxi Beijing
The 50th-75th quantile group	Shaanxi Chongqing Anhui Guangdong Hunan Liaoning Fujian
The 75th-90th quantile group	Henan Shangdong Hubei Sichuan Jilin
The upper 90th quantile group	Hebei Jiangsu Zhejiang

promoting technological innovation in emissions reduction. Thus, the effect of urbanization in the upper 90th quantile provinces is strongest in other quantile provinces.

3) The effects of energy intensity on CO_2 in the lower 10th and 10th-25th quantile provinces are lower than in other quantile provinces.

The results are mainly due to the difference between R&D funding and personnel investment. The positive coefficients of energy intensity in all quantile equations announces that energy savings and emission reduction technologies are not advanced in China, and haven't played an important role in declining CO_2. Only continuous R&D inputs can make it possible to acquire more advanced environmental technologies and achieve a substantial reduction in CO_2. Firstly, R&D funding plays an irreplaceable role in the process of scientific research [35]. The huge difference in R&D investment causes a differentiation of the advanced technology. In the period 2012-2016, the annual average R&D funding investment in in the lower 10th and 10th-25th quantile provinces are 0.88 and 5.3 (billion yuan), respectively, far smaller than those in the upper 90th quantile provinces (30.4), 75th-90th quantile provinces (29.88) and 50th-75th quantile provinces (14.13). Secondly, R&D personnel are the core elements for acquiring advanced technologies. Without talent, there is no vigor and source of technology. From 2004 to 2016, the average annual growth rate of R&D personnel in the lower 10th and 10th-25th quantile provinces was 18.65% and 19.23%, respectively, much lower than that in the upper 90th quantile provinces (42.57%), 75th-90th quantile provinces (29.44%), 50th-75th quantile provinces (36.15%), and 25th-50th quantile provinces (24.44%). Therefore, the energy intensity is smaller for the construction industry in the provinces below 0.1 and 0.1~0.25.

4) The effects of construction development on CO_2 emissions in the 25th-50th and upper 90th quantile provinces is greater than those in the other provinces.

This is mainly attributed to significant differences in the scale of the construction industry. The differences in construction business scale cause significant differences in the demand for energy consumption [36]. The output value of the construction industry requires frequent construction activities to achieve, in which building materials and mechanical equipment are necessary. The annual average per capita output of construction sector in the upper 90th and 25th-50th quantile provinces were 15.7 and 11.1 (thousand yuan), respectively, between 2004 and 2016, which were much higher than in the upper 75th-90th quantile provinces (6.3), 50th-75th quantile provinces (7.6), 10th-25th quantile provinces (4.0), the lower 10th quantile provinces (3.9). Therefore, the impact of the construction industry

Table 9. Estimation results: Quantile regression model and linear fixed effects model during the period from 2004-2016.

Variables	Quantile regressions					OLS
	10th quant	25th quant	50th quant	75th quant	90th quant	
Intercept	-5.6272***	-4.769***	-7.033***	-8.935***	-10.199***	-36.6839***
POP	1.1372***	1.1252***	1.2006***	1.3109***	1.3915***	2.2472***
URB	0.1768***	0.2961***	0.1884***	0.2327***	0.2898***	0.2710***
GDP	0.8193***	0.7624***	0.9678***	1.0876***	1.1562***	2.8374***
CA	1.1309***	1.1078***	1.1482**	1.1681***	1.0744***	0.7683***
ES	-0.0486**	0.0996 ***	0.0770***	-0.016**	-0.0006***	-0.0466***
EI	0.3366***	0.3621***	0.3719***	0.4617***	0.4925***	0.3286***
Pseudo R^2	0.8546	0.8331	0.8670	0.8120	0.8420	0.9131

Note: ***, ** indicate the parameters passed the significance test at the 1% level and the 5% level, respectively

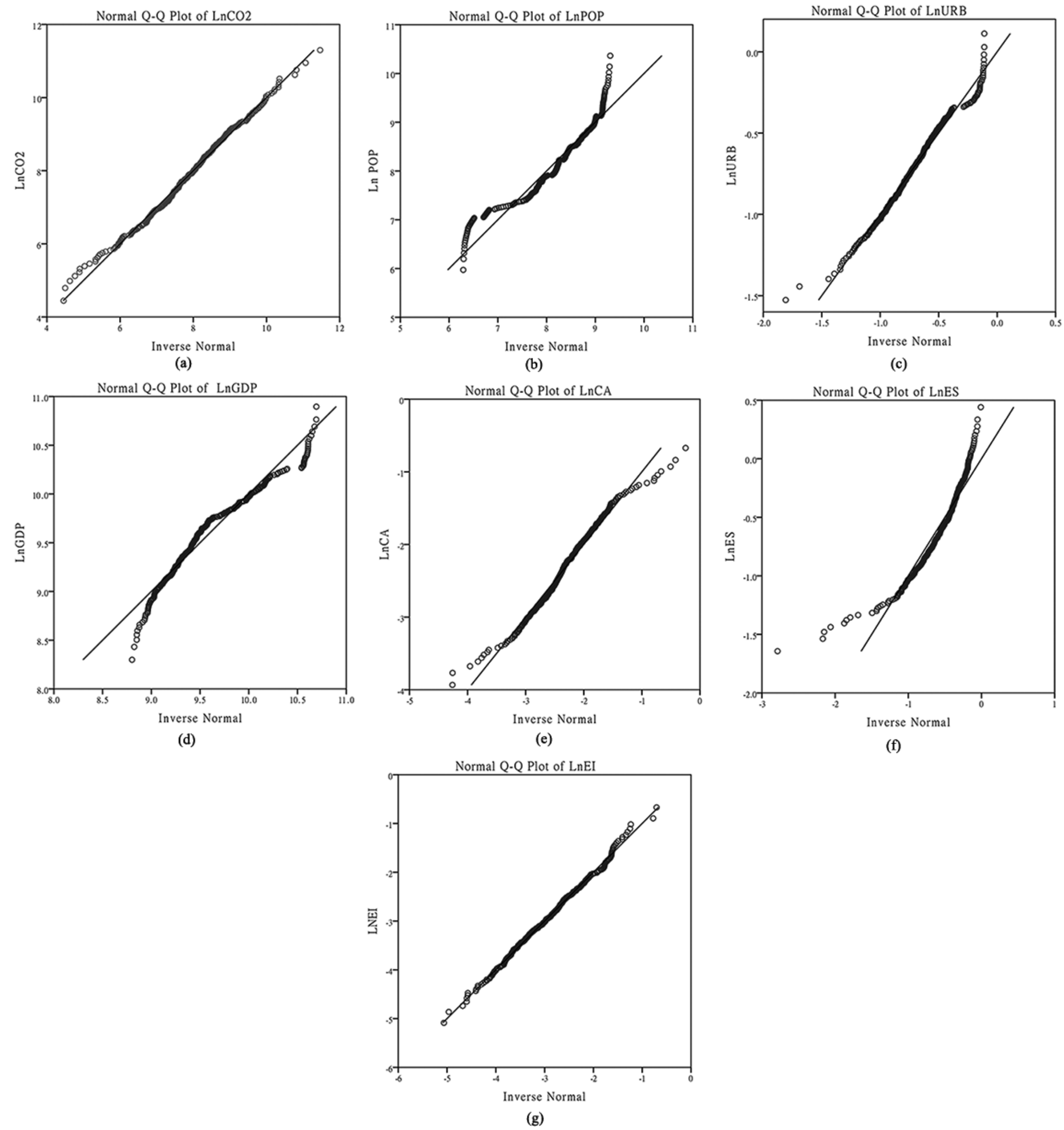

Fig. 4. The normal Q-Q plot of $LnCO_2$, LnGDP, LnURB, LnEI, LnCA, LnES and LnPOP.

expansion on CO_2 emissions in the upper 90th and 25th-50th quantile provinces is higher than those in other quantile provinces.

5) The impacts of energy structure on CO_2 emissions in the 10th-25th quantile provinces are highest in all the quantile provinces.

As far as we are concerned, the different impact of energy structure on CO_2 emissions mainly depends on the coal consumption in the construction industry. Rich reserves and low prices lead to coal being the main source of energy consumption in China for a long time [37]. During the period of 2012-2016, average coal consumption accounted for 67.9% of the total energy consumption in the 10th-25th quantile provinces, much higher than in the upper 90th quantile provinces (56.9%), 75th-90th quantile provinces (58.2%), 50th-75th quantile provinces (56.3%), 25th-50th quantile provinces (56.1%), lower 10th quantile provinces (50.2%). At the same time, except for 25th quantile provinces, the energy structure has a negative correlation with CO_2 emissions in other quantile provinces, stating clearly that energy structure optimization is helpful to reduce CO_2 emissions. This is mainly due to the reduction in the consumption of high-polluting coal and the increase in the utilization of clean energy. From 2012 to 2016 the proportion of coal consumption in the lower 10th, 10th-25th, 25th-50th, 50th-75th, 75th-90th, upper 90th quantile provinces decreased from 51.4%, 73.8%, 52.4%, 51.5%, 62.6%, 51.9% to 46.3%, 70.7%, 48.6%, 40.9%, 55.1%, 48.6%, respectively. In summary, optimizing energy structure can play a significant role in reducing CO_2 emissions in the construction industry.

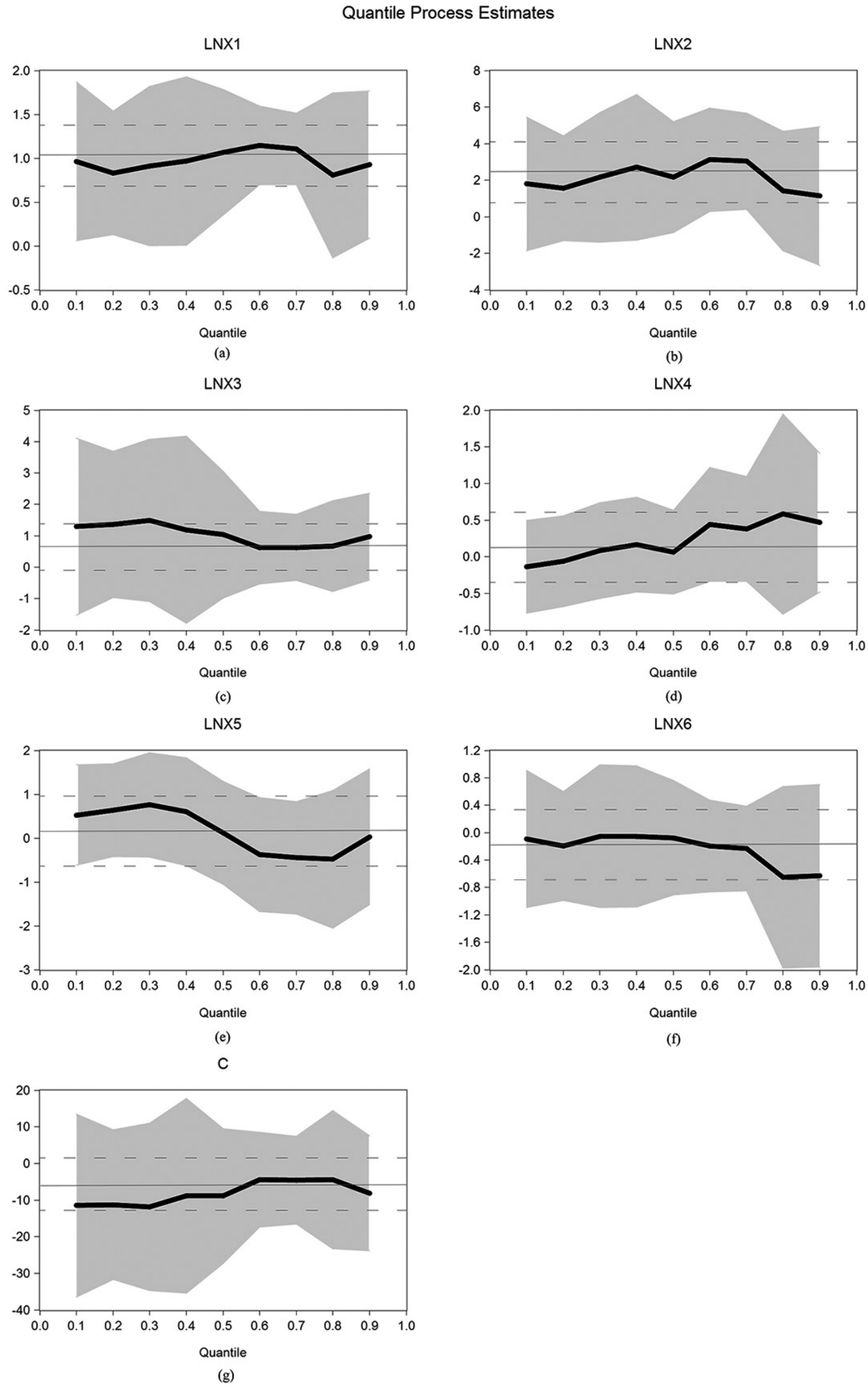

Fig. 5. Quantile estimate: The effects of driving forces on the construction sector's CO_2 emissions. Notes: Shaded areas represent 95% confidence band for the quantile regression estimates. The vertical axis indicates the elasticities of the explanatory variables. The red horizontal lines depict the conventional 95% confidence intervals for the OLS coefficient.

Conclusions and Policy

This paper analyzes the inter-provincial differences in china's construction sector CO_2 emssions from the perspectives of distribution and the driving factors. According to the annual CO_2 emission distribution, 30 provinces were divided into 6 groups, namely the lower 10th, 10th-25th, 25th-50th, 50th-75th,75th-90th and upper 90th quantile provinces. Using panel data from 2004 to 2015, this paper applies the quantile regression model to explore the main factors affecting CO_2 emissions in the 30 provinces' construction industries. Particularly, the dynamic varying process of their elastic coefficients at different quantiles is also presented. In addition, the results of OLS regression and quantile regression are compared to highlight the advantages of quantile regression. The main conclusions are as follows: (1) Results show that the construction industry is the main contributor to the national carbon emissions in China. CO_2 emissions from the construction industry grew rapidly at an average annual growth rate of 13% between 2004 and 2012, while it has begun to show a downward trend since 2012, which was developing toward benign direction. (2) Over the study period, the impact of six driving factors on CO_2 emissions from the construction sector in different regions existed with significant differentiations both in magnitude and in direction. (3) The results reveal that the elastic coefficient of each determinant differs distinctly at different quantiles, indicating that each factor has different effects on CO_2 emissions from the construction sector. According to the empirical results, the factors that drive the growth of CO_2 emissions from the construction sector in all provinces were population size, economic growth, construction development, and urbanization. On the contrary, the factors that mainly inhibited carbon emissions were energy structure and energy intensity. (4) Finally, compared with the traditional OLS, quantile regression can fully reveal the heterogeneous influence of explanatory variables on the different quantiles in the explained variable. Based on the above empirical results, this study puts forward corresponding countermeasures.

(1) The 10th-25th, 50th-75th and 75th-90th quantile provinces should adjust economic structure and promote the high technology industrial development. First, for a long time, economic structure is extremely unreasonable and excessive reliance on fixed asset investment, leading to the energy-intensive industries over-expanding. In order to effectively reduce CO_2 emissions from the construction industry, these quantile provinces are supposed to actively adjust their economic structures. Owing to the advantages of knowledge-intensive, innovative and low-carbon, the above provinces can vigorously promote the high-tech industrial development. Under serious environmental pollution, the high-tech industries can not only change the economic mode and promote sustainable growth, but also reduce energy consumption.

(2) The lower 10th and 10th-25th quantile provinces should further expand R&D expenditure and personnel investment in emission reduction technologies. Technological progress is the fundamental way to reduce CO_2 emissions [38]. Large-scale R&D funds and personnel investment are two indispensable elements of technological innovation. At present, China's R&D investment accounted for only 1.2% of GDP, which is much lower than in developed countries (5-10%). Therefore, local governments should set up special R&D investment funds to provide project funds for enterprises and institutions engaged in emission reduction technology research. At the same time, local governments should also encourage universities and research institutions to develop technicians. The main problem in the construction industry is the massive use of building materials. Local governments should encourage construction enterprises to adopt advanced technologies to reduce the use of high-energy building materials and accelerate the promotion of recyclable and renewable building materials. At the same time, it is necessary to strengthen the technology improvement in the production process of cement and steel. Steel enterprises should speed up the promotion and innovation of cinder circulation combustion technology, greatly improving the combustion efficiency of coal.

(3) The 25th-50th and upper 90th quantile provinces should optimize the construction structure and vigorously promote the utilization of composite materials. Reducing fixed assets investment to optimize the industrial structure, thereby reducing the demand on the building materials. Governments can formulate incentives and restrictive policies to slow down the population growth and housing demand, avoiding irreversible environmental damage in some provinces. Secondly, some foreign enterprises try to mix volcanic ash and slag with some additives to produce cement powder to replace the traditional cement clinker. Therefore, China's cement production enterprises should improve energy-saving cement research, or directly import foreign advanced technology. In addition, the construction industry should accelerate promoting the high-performance composite materials application and vigorously promote the construction of green low-carbon buildings.

(4) The 10th-25th quantile provinces should intensify efforts to optimize the energy structure. Coal dependence has led to massive CO_2 emissions in the construction industry. Local governments should not only control coal consumption, but also actively develop other clean energy sources. First of all, the government should levy an environmental compensation tax on coal production and consumption. This will not only raise money to restore the natural environment, but also promote the use of alternative energy. Secondly, China is a large agricultural country and produces a large amount of crop straw every year. Using crop straw to generate electricity can generate large amounts of electricity to meet energy needs. Therefore, local

governments should promote clean energy and guide the energy structure adjustment.

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Conflict of Interest

The authors declare no conflict of interest.

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