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A quantile regression analysis of China's provincial CO_2 emissions: Where does the difference lie?

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HIGHLIGHTS

- The driving forces of China's CO_2 emissions are investigated.
- Economic growth plays a dominant role in the growth of CO_2 emissions.
- The impact of urbanization increases from the lower 10th quantiles to the upper 90th quantiles.

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ABSTRACT

China is already the largest carbon dioxide emitter in the world. This paper adopts provincial panel data from 1990 to 2014 and employs quantile regression model to investigate the influencing factors of China's CO_2 emissions. The results show that economic growth plays a dominant role in the growth of CO_2 emissions due to massive fixed–asset investment and export trade. The influences of energy intensity on the lower 10th and upper 90th quantile provinces are stronger than those in the 25th–50th quantile provinces because of big differences in R&D expenditure and human resources distribution. The impact of urbanization increases continuously from the lower 10th quantile provinces to the 10th–25th, 25th–50th, 50th–75th, 75th–90th and upper 90th quantile provinces, owing to the differences in R&D personnel, real estate development and motor–vehicle ownership. The effect of industrialization on the upper 90th quantile provinces is greater than those on other quantile provinces on account of the differences in the industrial scale and the development of the building industry. Thus, the heterogeneity effects of influencing factors on different quantile provinces should be taken into consideration when discussing the mitigation of CO_2 emissions in China.

1. Introduction

Carbon dioxide (CO_2) produced by human activities has become a source of increasing global warming and environmental degradation (Xu and Lin, 2015a). According to the China Statistical Yearbook, in 2014, China's total CO_2 emissions reached 11.5 billion tons, accounting for 29% of the world's total emissions. Therefore, China has become a focus of global efforts to reduce CO_2 emissions amidst increasing international pressure. However, rigid energy demand continues to exist due to rapid industrialization and urbanization. This leads to difficulty in reducing CO_2 emissions. Thus, understanding and investigating the influencing factors of China's CO_2 emission is of vital importance (Den Elzen et al., 2016).

Given that rapid industrialization and urbanization lead to a surge in China's CO_2 emissions, many scholars have conducted extensive studies on the driving forces of CO_2 emissions from a national or regional perspective. To the best of our knowledge, China has a vast territory, with significant provincial differences in resources distribution and economic growth. Hence, the studies investigating the driving forces of CO_2 emissions from a national or a regional perspective ignore provincial heterogeneity, and result in a biased estimation (Lin and Wang, 2015). In addition, most of these studies only use linear models and ordinary least squares (OLS) to estimate the influences of the driving forces of CO_2 emissions. This has two shortcomings. On the one hand, a large number of nonlinear relationships embodied in economic variables are largely ignored. On the other hand, the OLS can only

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provide an average impact of the driving forces of CO_2 emissions without describing the effects of extreme values.

Because the quantile regression model cannot only capture a large number of nonlinear relationships between economic variables, but also effectively describe a complete picture of the heterogeneous effects of the driving forces, the paper uses it to investigate the driving forces of China's CO_2 emissions based on 30 provincial panel data over the period 1990–2014.

The remaining parts of the paper are organized as follows. Section 2 briefly reviews the related literature and previous studies on CO_2 emissions. Section 3 describes the applied method. Section 4 provides the results of the empirical analysis, and the conclusions and policy suggestions are provided in Section 5.

2. Literature review

The existing literature has extensively studied CO_2 emissions using different methods. The methods used to research CO_2 emissions are basically divided into four categories. The first and classical approach is the index decomposition. The CO_2 emissions are decomposed into economic growth, carbon intensity, energy structure and technological progress. Remuzgo and Sarabia (2015) studied the inequality in CO_2 emissions across different countries all over the world by technical efficiency, population and economic growth. Moutinho et al. (2015) extended the above analysis to renewable energy consumption and concluded that energy mix effect was one of the main drivers reducing CO_2 emissions for western, eastern, southern and northern European countries. Furthermore, economic structure was shown to contribute significantly to CO_2 emissions in Spain (Cansino et al., 2015) and in the United States (Shahiduzzaman and Layton, 2015). The second method is the bottom–up analysis. Di Cosmo and Hyland (2015) examined the effects of emission allowances on CO_2 emissions in Europe with an input–output method. Zhao et al. (2015a) developed an environmental input–output model to investigate CO_2 emissions in different industrial sectors in South Africa. The method was also used to survey the role of energy technology in reducing CO_2 emissions in Britain's upstream industries and Lebanese transport sector (Daly et al., 2015; Dhar and Marpaung, 2015). The third method is system optimization. This method has been widely applied in research on the reduction potential of energy demand and CO_2 emissions (Li et al., 2015a; Ou et al., 2015; Kang and Liu, 2015); integrated energy planning for sustainable development (Rietbergen et al., 2015; Yang et al., 2015a); and in investigating main factors influencing CO_2 emissions in Germany's electric vehicle (Jochem et al., 2015). The fourth method is econometric models. Using autoregressive distributed lag (ARDL) model, Sohag et al. (2015) examined the effect of household consumption on CO_2 emissions in Malaysia. Applying the ARDL model, Baek (2015) found Environmental Kuznets Curve (EKC) hypothesis does not exist in Arctic countries, and economic growth is conducive for environmental improvement in some Arctic countries. Marimoutou and Soury (2015) examines the interdependent relationship between CO_2 emission and energy prices with stochastic copula autoregressive model. Pablo-Romero et al. (2015) pointed out that urbanization is one of the main factors affecting energy consumption and carbon emissions in the transport sector using cross–sectional regression model. These methods are all parametric regression methods, which assumes the relationships between the variables in advance. Because these relationships are complex, artificially assuming these relationships is often inappropriate. Therefore, Ebrahimi and Salehi (2015) applied non–parametric Data Envelopment Analysis (DEA) to investigate the impact of technical and scale efficiency on CO_2 emissions in Iran's food industry. The results show that the role of technical efficiency in reducing CO_2 emissions of efficient and inefficient farmers is distinct.

With increasing CO_2 emissions and growing pressure surrounding emissions-mitigation, more attention has been focused on China. Using Logarithmic Mean Divisia Index (LMDI) decomposition method, Chen and Yang (2015) decomposed the change in China's CO_2 emissions into twelve driving forces such as labor productivity, energy intensity, population size, industrial structure and energy structure. Chang and Lahr (2016) and Liu et al. (2015) researched CO_2 emissions in the manufacturing industry and transport sector with a similar method. They emphasize that economic scale and energy intensity are the most important dominant factors for the change in the level of CO_2 emission. But, Yuan et al. (2015a) suggested that expanding urbanization and ongoing optimization of the energy structure play important roles in the growth of CO_2 emissions. Applying a bottom–up model, Mi et al. (2015) surveyed the influence of potential industrial structure on energy consumption and CO_2 emission in Beijing between 2010 and 2050, and suggested that industrial restructuring can save energy consumption worth of 50.06 million tons standard coal equivalent (tce) and mitigate CO_2 emissions by 96.31 million tons. Zhang et al. (2015a) estimates CO_2 emissions and mitigation potential in China's aluminum industry with a similar method. Their results show that improving energy–saving technologies and implementing alternative countermeasures are critical for reducing CO_2 emissions. Based on input–output tables, Jiang et al. (2015) concluded that international trade has a two–sided effect on China's CO_2 emissions. Xu et al. (2015a), Zhao et al. (2015b) and Xu and Lin (2016a) assessed the energy consumption and CO_2 emissions in different industrial sectors such as the steel, power and transport sectors in China, using the system optimization method. They found that energy–saving technology helps reduce CO_2 emissions, but urbanization plays an opposite role. By applying data envelopment analysis (DEA) model, Lin and Fei (2015) explored the effects of technological progress and technical efficiency on CO_2 reduction in China's agriculture sector and indicated that the two components play a key role in the final carbon emissions performance. Yang et al. (2015b), employing panel data models, also concluded that economic growth, income and urban population size are the main factors affecting carbon emissions in China's transport sector. Using similar model, Wang et al. (2015) and Ding et al. (2015) suggested that economic growth and increase in population have a positive effect, and technology improvement helps reduce China's CO_2 emissions. Yuan et al. (2015b), employing threshold regression model, also concluded that economic growth and urban population are the major determinants of CO_2 emissions. However, Wang and Zhao (2015) forecasted the trend of CO_2 emissions in China's six energy-intensive industries (e.g., cement, steel, transport sector) using Gray Forecast model (GM).

Though the driving factors of CO_2 emission have been discussed extensively, there are two main shortcomings. Firstly, China has a vast territory, with apparent regional differences in resource endowments, level of economic development and population distribution. However, most of the existing studies investigating the driving forces of CO_2 emissions from a national or regional perspective ignore provincial heterogeneity, thereby resulting in biased estimations. Secondly, most of these studies only use linear models and ordinary least squares (OLS) to estimate the influences of the driving forces of CO_2 emissions. This results in unreliable results as a large number of nonlinear relationships embodied in economic variables are largely ignored, and the effects of extreme values cannot be described. Granger (1988) points out that the world is almost certainly constituted by nonlinear relationships.

This study is different from previous researches in two aspects. The first is that this paper constructs a provincial panel data set to