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Transmission mechanism between energy prices and carbon emissions using geographically weighted regression

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ABSTRACT

This work quantifies the conduction mechanism of energy prices on carbon emissions and carbon intensity from the perspective of space and quantile. Taking China's Eight Economic Regions as an example, we explore how to optimize energy price policy to promote regional carbon reduction by combining the GWR model, quantile regression and scenario analysis. The study finds that (1)the energy prices can promote or suppress carbon emissions and carbon intensity through five variables, including economic development, industrial structure, energy efficiency, energy investment and energy consumption etc.(2) the current energy investment and consumption structure lead to a high level of carbon emissions, while such effect from economic development is relatively limited, and the influence direction and level of industrial structure and energy efficiency on carbon emissions are regionally different. (3) with the exception of the energy consumption structure, four other factors have varying restraining effects on carbon intensity, and (4) scenario analysis shows that optimizing industrial and energy consumption structure are crucial to reduce carbon emissions , and optimizing industrial structure helps to reduce carbon intensity. Finally, this paper proposes policy suggestions, aiming to realize regional carbon reductions by using price leverage.

1. Introduction

Climate change and Greenhouse Gas (GHG) emissions threaten our way of life. To begin to address this problem, the Intergovernmental Panel on Climate Change (IPCC) has advocated that increases in average global temperature levels should not be allowed to exceed 2 ℃ during the twenty-first century, and in doing so, has severely constrained the room available for carbon emissions in each country (Pan et al., 2014; Dong et al., 2016a, 2016b). However, in recent years, following rapid economic growth especially in developing countries, the consumption of fossil fuels has continued to go uncontrolled, and has led to unexpectedly high levels of carbon emissions (Chen et al., 2015; Lin et al., 2012; Yang et al., 2016; Wang et al., 2016; Zhu et al., 2017). An important question that has subsequently emerged is how to control and reduce carbon emissions efficiently, while simultaneously maintaining a sound rate of economic development. Some scholars have proposed that energy prices are the most basic and effective means of deciding resource allocations, and balancing energy conservation and carbon emissions (He et al., 2013; Dong et al., 2017). Thus, the role of energy prices in this issue deserves to be reconsidered.

As was to be expected, the reform of the energy price system—-which includes coal, oil, and natural gas—was influenced and dramatically accelerated by the international energy market. For example, with regard to China's coal price reforms, the price adjustment mechanism for everything from the planned price system to the market price system has been re-established as a result of the implementation of the reform and the opening-up policy in 1987. Moreover, with regard to the oil price reform, since 2009 China has linked domestic refined oil prices with international crude oil prices according to their real-time fluctuations. Furthermore, with regard to the natural gas price reform, which resembled the coal price reform, the domestic price was set by the government before 1987, which then became more liberalized based on its guidance. In addition, after a long period of improvement, at the beginning of 2016, the *Development and Reform Commission of China* introduced the *Oil and Gas System Reform Overall Program*, thereby initiating a new round of reforms in the energy price system. Further, during the 13th Five-Year Plan period (2016–2020), the price of energy products (such as oil, gas, and electricity) would be further liberalized by the *Opinions on Promoting the Reform of Pricing Mechanisms*. Therefore, it is imperative that the current mechanism on

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energy prices be investigated to enable the government to document its functions in the reduction of carbon emissions.

Some scholars have pointed out that energy prices have a direct impact on carbon emissions (Vanden et al., 2004; Lee and Zhang, 2012; Lin et al., 2012; Liu et al., 2015; Apergis and Payne, 2015; Alshehry and Belloumi, 2015; Dong and Gao, 2016; McCollum et al., 2016; Zhang et al., 2017a). They have explained that the effects of energy prices on market allocations could promote industrial agglomeration and accelerate technological spill over or information exchange among industries, thereby motivating the energy industry to be greener and more efficient. Absolute market allocation, however, would also impose the risk of a financial crisis on the energy industry. Alternatively, other scholars argue that there is a conductive effect (indirect impact) between energy prices and carbon emissions. For example, Lahiani et al. (2017) posited that there is a transfer process, namely, 'Energy price (tools) - The relevant dimension factors (path) - Carbon emissions (target)'. Moreover, it has been shown that paths between energy prices and carbon emissions are not unique, and that the conductive factors are mainly focused on economic developments/economic outputs (Tahvonen and Salo, 2001; Abeysignhe, 2001; Dong et al., 2013b), industrial structures (Cuñado, 2003; Wang et al., 2009), energy efficiencies (Birol and Kepple, 2000; Cohen et al., 2015; Jacobsen, 2015), energy consumption structures/energy structures (Abolhosseini et al., 2014; Lee and Chong, 2016), and technological progress (Zhang et al., 2016).

Furthermore, to confirm such a mechanism, a number of factors and methods have been tested. Birol and Kepple (2000) tested energy efficiency and energy intensity; Nag and Parikh (2000) used structural changes, activity levels, and energy intensity; Mahony et al. (2012) selected the economic scale, energy structure, and energy intensity; Olatunji et al. (2014) chose income, energy consumption, and technological progress; Lee and Chong (2016) harnessed an energy consumption structure; Li et al. (2017a) chose per capita GDP, total societal investment and total factor productivity; and He et al. (2017) examined energy efficiency and prices. A ridge regression model (Dong et al., 2016a, 2016b), a granger test (Lee and Chong, 2016), a stochastic frontier model (Dong et al., 2013a), and a hierarchical clustering method (Deviren and Deviren, 2016) have been used to study this topic. However, their empirical results are mostly based on mean data. They do not explore the characteristics of all sides of different data structures, and some highly valuable sub-site characteristics and/or extreme value characteristics are easily overlooked.

When dealing with problems such as regional issues in practice, it may be difficult to obtain a comprehensive result, since different regions face different situations that will not be disclosed using only mean values. For instance, some scholars explored the regional emissions from eastern or western China (Guo and Chen, 2014; Dong et al., 2017; Li et al. 2017b) or other macro perspectives. Unfortunately, their regional differences are usually not calculated or emphasized. To address this problem, this work combines the quartile regression principle with the GWR model, and comprehensively investigates impact mechanisms between energy prices and carbon emissions that occur through five main regulatory factors—economic development, energy investment, industrial structure, energy efficiency, and energy consumption structures—and applies its analysis to China's Eight Economic Regions based on provincial panel data from 1997 to 2014. Next, a comprehensive study of the impact mechanism between energy prices and carbon emissions is conducted from different quartile perspectives. This paper explores the potential impact of carbon emission reductions on each region using the scenario analysis method, hoping to provide a theoretical basis and decision-making reference for the formulation of regional energy prices and a carbon emissions reduction policy.

Overall, this work is presented as follows: Section 2 introduces the methodology, including the GWR model, model settings, and data sources. Section 3 presents the results and discussion, and analyses the impacts of energy prices on carbon emission reductions based on the GWR model; using scenario analysis, it also identifies the regulatory factors that optimized carbon emission reductions in different regions. The study's main conclusions and anticipated policy implications are provided in Section 4.

2. Methodology

In this section, we use a geographically weighted regression model and quartile regression principle to conduct a multi-level analysis of the effects of energy prices on carbon emissions in China, from the perspective of spaces and quartiles.

2.1. Geographically weighted regression model

The Geographical Weighted Regression (GWR) model is a nonparametric estimation method based on the local weighted least squares regression model. It effectively deals with the coexistence of spatial correlation and spatial heterogeneity. In this paper, the heterogeneity characteristics of the driving factors of carbon emissions reduction are described by GWR (LeSage, 2004) in the theory of spatial econometrics. GWR explores the differences in various spatial locations, and is widely used in real estate, agriculture, and economics. The central idea of GWR is to incorporate the geographic coordinates of data into the regression parameters. It estimates the local regression by analysing sub-sample data for adjacent observations, and the parameters of changing local spatial geographic locations. The GWR depicts the spatial mechanisms of carbon reduction behaviours of different local governments in relation to changes in geographic distance, especially with regard to regional spatial effects between neighbouring provinces due to lower spatial transaction costs (Wu and Li, 2009). The models are as follows:

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_{i=1}^{k} \beta_k(\mu_i, \nu_i)x_{ik} + \varepsilon_i \tag{1}$$

y_i is an $n \times 1$ dimensional interpretation variable; x_{ik} is a $n \times k$ dimensional interpretation variable matrix; $\beta_k(\mu_i, \nu_i)$ ($k = 1,2,3,\ldots$) is the regression coefficient of factor k at the regression point, (μ_i, ν_i) represents the longitude and latitude coordinates at the i^{th} observation point, and ε_i is the random error term of the independent distribution.

The spatial weighting coefficient is determined by the Gaussian kernel function (Xuan et al., 2016), which makes the model easy to solve. The Gaussian function determines the weight function as:

$$\omega_{ij} = \exp(-\frac{d_{ij}^2}{b^2}) \tag{2}$$

b is the bandwidth, and d_{ij} is the direct distance between the sample points $_i$ and$_j$. If the data of i is observed, the weight of the other points decreases when d_{ij} increases, according to the Gaussian Curve. When given the value of b, the larger the distance d_{ij}, the smaller the weight given by position j would be. The weight tends to be zero if it is far enough from point i.

In the following steps, the optimal bandwidth is selected using the Cross Validation method, and we set the model to have the same window-width parameter at each quantifier, for purposes of comparison and calculation.

$$CV = \sum_{i=1}^{n} [y_i - \hat{y}_{\neq i}(b)]^2 \tag{3}$$

y_i shows the actual observed value of the explained variable Y at point (μ_i, ν_i); $\hat{y}_{\neq i}$ represents the set value when the window width parameter b is fixed, and the actual observed value is removed; when the CV minimum value is taken, the optimal bandwidth and the corresponding time weight matrix are solved. At this point, the model of simplification and solution calculated by ArcGIS 10.2 is complete.