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A dynamic analysis of air pollution emissions in China: Evidence from nonparametric additive regression models

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ABSTRACT

$PM_{2.5}$ emissions not only have serious adverse health effects, but also impede transportation activities, especially in air and highway transport. As a result, $PM_{2.5}$ emissions have become a public policy concern in China in recent years. Currently, the vast majority of existing researches on $PM_{2.5}$ are based on natural science perspective. Very few economic studies on the subject have been conducted with linear models. This paper adopts provincial panel data from 2001 to 2012, and uses the STIRPAT model and nonparametric additive regression models to examine the key driving forces of $PM_{2.5}$ emissions in China. The results show that the nonlinear effect of economic growth on $PM_{2.5}$ emissions is consistent with the Environmental Kuznets Curve (EKC) hypothesis. The nonlinear impact of urbanization exhibits an inverted "U-shaped" pattern due to the rapid development of urban real estate in the early stages and the strengthening of environmental protection measures in the latter stage. Coal consumption follows an inverted "U-shaped" relationship with $PM_{2.5}$ emissions owing to massive coal consumption at the beginning and efforts to optimize the energy structure as well as technological progress in clean energy in the latter stages. The nonlinear inverted "U-shaped" impact of private vehicles may be due to the different roles of scale, structural and technical effects at different stages. However, energy efficiency improvement follows a positive "U-shaped" pattern in relation to $PM_{2.5}$ emissions because of differences in the scale of the economy and the speed of technological progress at different times. As a result, the differential dynamic effects of the driving forces of $PM_{2.5}$ emissions at different times should be taken into consideration when initiating policies to reduce $PM_{2.5}$ emissions in China.

1. Introduction

China is currently in a rapid urbanization and industrialization process (Xue et al., 2015). There is rapid increase in the number of motor vehicles as well as energy consumption (e.g., coal), coupled with large-scale fixed asset building activities (Zhang and Cao, 2015). These activities are exposing China to large-scale, severe and persistent air pollution problems (Meng et al., 2015). Numerous studies have demonstrated that $PM_{2.5}$ (fine particles) is the main cause of air pollution (Wang et al., 2015a). $PM_{2.5}$ not only includes many small particles such as organic carbon, nitrates, ammonium salts and sulfates, but also includes various metal elements such as sodium, magnesium, calcium, aluminum, zinc, arsenic, cadmium and copper (Zhao et al., 2014; Huang et al., 2014). These small particles are easily inhaled, and may pose health risks by contaminating the blood (Yang et al., 2013). $PM_{2.5}$ pollution caused about 1.25 million deaths in China in 2010, accounting for nearly 40% of the global total premature deaths (Wang et al., 2012). Therefore, $PM_{2.5}$ emissions have become an urgent issue of public concern in recent years.

$PM_{2.5}$ emissions have been analyzed extensively in the literature (Mallia et al., 2015; Mardones and Sanhueza, 2015; Meng et al., 2015; Zhang and Cao, 2015). Most of the existing studies only use linear models to analyze the influences of the driving forces of $PM_{2.5}$ emissions. In fact, there are a large number of linear and nonlinear relationships between economic variables (Catalano and Figliola, 2015).

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The paper is concerned with the impacts of the driving forces of $PM_{2.5}$ emissions in China at the aggregate level. Using a panel data set covering 29 provinces over the period 2001–2012, we employ the STIRPAT model and nonparametric additive regression models to explore the effects of the influencing factors of $PM_{2.5}$ emissions in China. Non-parametric additive can capture the linear and nonlinear links between economic variables.

The remaining parts of the paper are organized as follows. Section 2 briefly reviews the related literature and previous studies on $PM_{2.5}$ emissions. Section 3 describes the applied method and the model. Section 4 presents the empirical results. Section 5 discusses the results of the empirical analysis. Conclusions and policy suggestions are provided in Section 6.

2. Literature review

$PM_{2.5}$ pollution is a natural phenomenon, but it is a man-made contamination caused by human economic activities (Mardones and Sanhueza, 2015). Therefore, from an economic and social point of view, analyzing the main driving forces of $PM_{2.5}$ emissions is conducive for reducing $PM_{2.5}$ emissions and stemming its hazardous impacts on human health. The existing literature has extensively studied $PM_{2.5}$ emissions with different methods.

Firstly, the classical method is structural decomposition analysis. $PM_{2.5}$ emissions are decomposed into economic growth, capital formation, exports, production structure and emission intensity. Guan et al. (2014) research $PM_{2.5}$ emissions growth in China by analyzing economic growth, fixed asset investment and exports, and Djalalova et al. (2010) extend the research to emission intensity and decompose $PM_{2.5}$ emissions into energy intensity, energy structure and conversion efficiency for Europe. The second method is bottom-up sector-based analysis. Zhang et al. (2015) investigate $PM_{2.5}$ pollutants emissions in the metropolis using a top-down approach. Liu et al. (2014) develop an integrated assessment model to analyze air pollutants from China's iron and steel industry, and find that command-and-control instrument has excellent impact in controlling pollutants emissions. The method is also used in the study of energy consumption (Cai et al., 2015; Farzan et al., 2015) and CO_2 emissions (Zhang and Chen, 2014; Tang et al., 2015). The third method is dynamic factor analysis (DFA). It has been widely applied in the analysis of the influencing factors of air pollutants (Shi et al., 2008; Ielpo et al., 2013; Yu et al., 2015) and in forecasting macroeconomic variables (Brauning and Koopman, 2014; Palardy and Ovaska, 2015). The fourth method is econometric model. Using panel econometric models, Loftus et al. (2015) study $PM_{2.5}$ emissions in American agricultural areas; Olson and Burke (2006) research the seasonal variation and factors of $PM_{2.5}$ emissions; and Sica and Susnik (2014) investigate the relationships between economic growth and $PM_{2.5}$ contaminants with provincial data in Italy. Patel et al. (2013), Bozlaker et al. (2014) and Shen et al. (2014) examine the effects of different means of transport on $PM_{2.5}$ emissions, and found the extensive use of motor vehicles has become one of the main sources of $PM_{2.5}$ emissions. Khan et al. (2015) determine the major factors of $PM_{2.5}$ emissions using time series models.

Though $PM_{2.5}$ emissions have been discussed extensively in the literature, there is a major shortcoming. In other words, most of these studies only use linear models to analyze the influence of the driving forces of $PM_{2.5}$ emissions. Nonlinear relationships embodied in economic variables are largely ignored. Granger (1988) pointed out that the world is almost certainly constituted by nonlinear relationships. In this paper, we investigate the linear and nonlinear effects of the influencing factors of $PM_{2.5}$ emissions using nonparametric additive regression model, since it can capture the linear and nonlinear linkages between economic variables.

3. Methodology and model specification

3.1. Nonparametric additive regression models

Nonlinear thinking refers to a kind of thinking that differs from linear thinking. That is, it looks at things from an unconventional perspective, such as systems thinking, fuzzy thinking and so on (Costigan and Brink, 2015). It probably will not follow normal logical thinking.

In a system, if the output is not proportional to its input, it is nonlinear. In fact, almost all known systems, regardless of whether they are natural sciences or social sciences, are non-linear, if the input amount is large enough (Islam et al., 2015). Therefore, non-linear systems are much more than linear systems. The real world has always been a non-linear system, and a linear system is only an approximate simulation (Cheung et al., 2015). For a nonlinear system, even a small disturbance, such as a small change in the initial conditions, is likely to cause great difference in system behavior in the next moment (Ide and Wiggins, 2015).

Similarly, every 1% increase in urbanization, economic growth, private cars, technological progress and coal consumption does not guarantee the same amplitude changes in $PM_{2.5}$ emissions. That is, there may be non-linear relationships between these factors and $PM_{2.5}$ emissions. This has been confirmed by numerous studies (Sueyoshi and Yuan, 2015; Salazar et al., 2011; Ning et al., 2015; Zhou et al., 2014). Nonparametric regression model is a data-driven model, and the relationships between the variables are portrayed by the sample data itself (Lee and Robinson, 2015). Compared to the linear models, the advantages of nonparametric additive regression model are obvious. First, it does not require pre-set relationships between the variables, and the regression functional form is not constrained (Curtis et al., 2014). Second, it has strong adaptability and high robustness, and the specific forms of the regression models are completely determined by the sample data itself, i.e., the non-parametric regression models are data-driven models (Piegorsch et al., 2014). Third, for non-linear non-homogeneous problems, non-parametric regression models have very good simulation results (Zhou et al., 2011). Fourth, the nonparametric additive regression models belong to a data-driven model. It does not make any prior assumptions on the relationships between economic variables. So there is a low possibility for over-fitting problem in this model, which will reduce or destroy the generalization ability of the model application (Farias et al., 2013). Consequently, we employ nonparametric additive regression models to capture the linear and nonlinear impacts of the driving forces of $PM_{2.5}$ emissions in China in this paper.

Additive regression models were first proposed by Stone in 1985. In additive regression models, the dependent variable Y_i (i = 1, 2, n) is the sum of arbitrary functions f_j (j = 1, 2,. . .,p), which are the functions of the independent variables X_{i1}, X_{i2}. . .,X_{ip}, respectively. Its specific form is:

$$Y_i = \sum_{j=1}^{p} f(x_{ij}) + \mu_i,\ \mu_i \sim iid(0, \sigma^2) \tag{1}$$

where $f(x_i)$ is a nonparametric function and can be estimated with nonparametric regression methods. In order to make the estimation feasible, it is assumed that $E(f_j) = 0$ (j = 1, 2,. . .,p) and f_j are smooth. In addition, the additive regression models can be expressed as:

$$E(Y_i | x_{i1}, x_{i2}, \ldots, x_{ip}) = \sum_{j=1}^{p} f(x_{ij}) \tag{2}$$

From Eq. (2), it can be seen that additive regression model is an improvement on linear models, where each explanatory variable is