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Forecasting China's regional energy demand by 2030: A Bayesian approach

Xiao-Chen Yuan[a,b,*], Yi-Ming Wei[b,e,*], Zhifu Mi[f,*], Xun Sun[c,d], Weigang Zhao[b,e], Bing Wang[b,g]

[a] Donlinks School of Economics and Management, University of Science and Technology Beijing, Beijing 100083, China
[b] Center for Energy and Environmental Policy Research, Beijing Institute of Technology, Beijing 100081, China
[c] School of Geographic Sciences, East China Normal University, Shanghai 200241, China
[d] Columbia Water Center, Columbia University, New York, NY 10027, USA
[e] School of Management and Economics, Beijing Institute of Technology, Beijing 100081, China
[f] School of Construction and Project Management, The Bartlett School, University College London,1-19 Torrington Place, WC1E 7HB, London, UK
[g] School of Resources and Safety Engineering, China University of Mining and Technology (Beijing), Beijing 100083, China

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ABSTRACT

China has been the largest energy consumer in the world, and its future energy demand is of concern to policy makers. With the data from 30 provinces during 1995–2012, this study employs a hierarchical Bayesian approach to present the probabilistic forecasts of energy demand at the provincial and national levels. The results show that the hierarchical Bayesian approach is effective for energy forecasting by taking model uncertainty, regional heterogeneity, and cross-sectional dependence into account. The eastern and central areas would peak their energy demand in all the scenarios, while the western area would continue to increase its demand in the high growth scenario. For the country as a whole, the maximum energy demand could appear before 2030, reaching 4.97/5.25 billion tons of standard coal equivalent in the low/high growth scenario. However, rapid economic development would keep national energy demand growing. The proposed Bayesian model also serves as an input for the development of effective energy policies. The analysis suggests that most western provinces still have great potential for energy intensity reduction. The energy-intensive industries should be cut down to improve energy efficiency, and the development of renewable energy is essential.

1. Introduction

China has been the largest energy consumer in the world, and its future energy demand is of concern to police makers due to the significance for strategic planning. In 2015, China's energy consumption totaled 4.30 billion tons of standard coal equivalent (SCE) of which coal accounted for 64.0%. The desire for strong economic growth as well as the ongoing processes of industrialization and urbanization will contribute to the increased energy use which eventually exerts pressure on the security and environmental issues (Chen et al., 2017; Hao et al., 2015; Jiang and Lin, 2012; Mi et al., 2016). Especially, in recent years, some ambitious carbon reduction targets have been explicitly proposed by China. This implies that more efforts may be needed to control the total amount of energy consumption so as to peak carbon dioxide emissions around 2030 (Mi et al., 2017). As a result, from a policy perspective it is imperative to investigate the potential ranges of energy demand in China (Brockway et al., 2015).

For medium- and long-term energy demand prediction, we argue that there is a need for informative estimates by integrating various information. This can be specified in the following ways. First, the analysis of energy use at the regional level is more useful. The regional pattern of energy demand would help make reasonable and specific policies since there are different situations across regions. Besides, it is suggested by You (2013) that the disaggregated information could improve the accuracy of energy demand forecasts. Second, it is of necessity to detect the uncertainty of energy demand predictions with regard to model estimation and possible adjustments of development polices. The possible range of energy demand could advance policy-making (Shao et al., 2015). Third, a combination of forecasts would make full use of the information carried by individual models, which is assumed to have a better predictive performance. When uncertainty is under consideration, incorporating probabilistic forecasts eventually presents a mixture distribution of energy demand that is supposed to be more reliable.

Previous studies employed various methods for energy forecasting (Suganthi and Samuel, 2012). Table 1 indicates that grey models and statistical models are more concise and less data/parameter-intensive. In particular, statistical approaches are easily applied to the analysis with multi-level information and provide an opportunity to estimate model uncertainty in a formal way. In practice, it is common to predict

* Corresponding authors.
E-mail addresses: xc.yuan@outlook.com (X.-C. Yuan), wei@bit.edu.cn (Y.-M. Wei), Z.Mi@uea.ac.uk (Z. Mi).

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Table 1
Comparisons of energy demand forecasting models.

Classification	Example	Model complexity	Data/parameter requirement
Bottom-up models	MARKAL (Tsai and Chang, 2015) TIMES (Comodi et al., 2012) LEAP (Kumar, 2016)	High level	High level
Intelligent models	ANN (Gunay, 2016) PSO (Ünler, 2008) GA (Li et al., 2015)	High level	High level
Grey models	GM(1,1) (Hamzacebi and Es, 2014)	Low level	Low level
Hybrid models	MPSO-RBF (Yu et al., 2012) GP-GM (Lee and Tong, 2011)	High level	High level
Statistical models	ARIMA (Yuan et al., 2016) Econometric model (You, 2013) Semiparametric model (Shao et al., 2015)	Low level	Low level

energy demand on the basis of the developed statistical relationship and the identified driving factors.

At present, traditional statistical techniques in the literature have not considered the uncertainties in the structural relations for energy estimation. Besides, they often use the common coefficient of regions for prediction at the sub-national level without fully accounting for heterogeneity. These problems make it difficult to obtain reasonable ranges of the estimated energy demand. Recent studies indicate that hierarchical Bayesian approach well addresses the uncertainties of model and parameter and provides for partial pooling of the common information from different regions while considering heterogeneity (Gelman and Hill, 2007). Moreover, it could flexibly model the dependence between variables to improve estimation. Therefore, this could help present the informative results of future energy demand so as to give useful insights for energy policies.

This paper aims to forecast China's energy demand and the associated uncertainties at the provincial and national levels. Our study contributes to the existing literature by formally modeling the uncertainties in the structural relations for energy estimation while considering regional heterogeneity and cross-sectional dependence, and offering a predictive distribution of energy demand.

2. Methodology

2.1. Influencing factors of energy use

The possible influencing factors of energy consumption has been extensively investigated in the literature. The major classifications are drawn as follows.

(1) *Economic level*. It shows that economic activity is a major contributor to energy consumption (Liao et al., 2016). Zhang and Xu (2012) examine the causal relationship between energy consumption and economic growth, and find that economic growth causes more energy consumption in China not only at the national level but also at the regional and sectoral levels. Furthermore, some studies indicate that there is a potentially nonlinear effect of economic development on energy consumption (Yoo and Lee, 2010; You, 2013).
(2) *Industrial structure*. There are significant differences in the energy consumed by industries. Especially, heavy industry is a primary consumer. It is commonly viewed that industrialization increases energy consumption (Sadorsky, 2014). However, Li and Lin (2015) find negative effects for both middle-/low-income and high-income groups. This suggests that the change in industrial structure caused by development would affect the pattern of energy use.
(3) *Demographic change*. The demographic factor (e.g. population and age structure) is an essential role considered for energy use in the literature (Liddle, 2014). Liu et al. (2015) find that the negative effect of population density on energy consumption vary across regions of China. The given interpretation is the result of modernization.
(4) *Urbanization process*. The inconsistent findings exist in the historical studies (Al-mulali et al., 2012; York, 2007). Poumanyvong and Kaneko (2010) show that urbanization decreases energy use in the low-income group, while it increases energy use in the middle- and high-income groups. The reduction is interpreted as the effects of fuel switching from inefficient traditional fuels to efficient modern fuels. However, development raises the use of private and public infrastructure so that more energy resources are required to support urban population and urban economies.
(5) *Technological progress*. The advancement of technology has impacts on energy efficiency and energy structure. These are essential for energy consumption. To cope with climate change, there is a need of new technologies to change the pattern of energy use in the future.

Based on the identified influencing factors, the research framework of this study for forecasting regional energy demand in China is shown as Fig. 1. The causal effects of influencing factors on energy consumption are constructed by hierarchical Bayesian approach which accounts for the uncertainties in the structural relations with regional heterogeneity and cross-sectional dependence. The estimated region-specific regression coefficients are used to obtain the energy demand predictions with uncertainty bounds. On the basis of individual models, the mixed probabilistic forecasts for energy demand with the specified development scenarios are made. We attempt to investigate the regional and national patterns of energy demand, the changes in energy intensity, and the impacts of energy structure adjustment.

2.2. Hierarchical Bayesian model

The empirical model for energy consumption per capita is shown as Eq. (1). For the gth group ($g = 1,2,\ldots G$) of $S^{(g)}$ provinces in year t, the energy consumption per capita $(y_{1t}, y_{2t}, \ldots, y_{S^{(g)}t})$ (log transformed) is modelled with a multivariate normal distribution which considers the dependence across provinces in group g.

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ \ldots \\ y_{S^{(g)}t} \end{pmatrix} \sim MVN\left(\begin{matrix} \alpha_1 + x_{1,1t}\beta_{1,1} + x_{2,1t}\beta_{2,1} + \ldots + x_{J,1t}\beta_{J,1} \\ \alpha_2 + x_{1,2t}\beta_{1,2} + x_{2,2t}\beta_{2,2} + \ldots + x_{J,2t}\beta_{J,2} \\ \ldots \\ \alpha_{S^{(g)}} + x_{1,S^{(g)}t}\beta_{1,S^{(g)}} + x_{2,S^{(g)}t}\beta_{2,S^{(g)}} + \ldots + x_{J,S^{(g)}t}\beta_{J,S^{(g)}} \end{matrix}, \Sigma_g\right) \tag{1}$$

where $\mathbf{x}_{st} = (x_{1,st}, x_{2,st}, \ldots, x_{J,st})$ is a set of J explanatory variables associated with energy consumption per capita of province s ($s = 1,2,\ldots S^{(g)}$) in year t. The regression coefficients $\beta_s^{(g)} = (\beta_{1,s}, \beta_{2,s}, \ldots, \beta_{J,s})$, the