

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

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1 **Forecasting China's regional energy demand by 2030: a Bayesian**  
2 **approach**

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16 ***Abstract***

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

29 ***Keywords:*** *energy demand; model uncertainty; Bayesian; forecast*

30 **1 INTRODUCTION**

31 China has been the largest energy consumer in the world, and its future energy demand is of concern to  
32 policy makers due to the significance for strategic planning. In 2015, China's energy consumption totaled  
33 4.30 billion tons of standard coal equivalent (SCE) of which coal accounted for 64.0%. The desire for  
34 strong economic growth as well as the ongoing processes of industrialization and urbanization will  
35 contribute to the increased energy use which eventually exerts pressure on the security and environmental  
36 issues (Chen et al., 2017; Hao et al., 2015; Jiang and Lin, 2012; Mi et al., 2016). Especially, in recent  
37 years, some ambitious carbon reduction targets have been explicitly proposed by China. This implies that  
38 more efforts may be needed to control the total amount of energy consumption so as to peak carbon dioxide  
39 emissions around 2030 (Mi et al., 2017). As a result, from a policy perspective it is imperative to  
40 investigate the potential ranges of energy demand in China (Brockway et al., 2015).

41 For medium- and long-term energy demand prediction, we argue that there is a need for informative  
42 estimates by integrating various information. This can be specified in the following ways. First, the  
43 analysis of energy use at the regional level is more useful. The regional pattern of energy demand would

44 help make reasonable and specific policies since there are different situations across regions. Besides, it  
 45 is suggested by You (2013) that the disaggregated information could improve the accuracy of energy  
 46 demand forecasts. Second, it is of necessity to detect the uncertainty of energy demand predictions with  
 47 regard to model estimation and possible adjustments of development polices. The possible range of energy  
 48 demand could advance policy-making (Shao et al., 2015). Third, a combination of forecasts would make  
 49 full use of the information carried by individual models, which is assumed to have a better predictive  
 50 performance. When uncertainty is under consideration, incorporating probabilistic forecasts eventually  
 51 presents a mixture distribution of energy demand that is supposed to be more reliable.

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

57 **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

58

59 At present, traditional statistical techniques in the literature have not considered the uncertainties in the  
 60 structural relations for energy estimation. Besides, they often use the common coefficient of regions for  
 61 prediction at the sub-national level without fully accounting for heterogeneity. These problems make it

62 difficult to obtain reasonable ranges of the estimated energy demand. Recent studies indicate that  
63 hierarchical Bayesian approach well addresses the uncertainties of model and parameter and provides for  
64 partial pooling of the common information from different regions while considering heterogeneity  
65 (Gelman and Hill, 2007). Moreover, it could flexibly model the dependence between variables to improve  
66 estimation. Therefore, this could help present the informative results of future energy demand so as to  
67 give useful insights for energy policies.

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

## 72 **2 METHODOLOGY**

### 73 **2.1 Influence factors of energy use**

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

76 (1) *Economic level*. It shows that economic activity is a major contributor to energy consumption (Liao et  
77 al., 2016). Zhang and Xu (2012) examine the causal relationship between energy consumption and  
78 economic growth, and find that economic growth causes more energy consumption in China not only at  
79 the national level but also at the regional and sectoral levels. Furthermore, some studies indicate that there  
80 is a potentially nonlinear effect of economic development on energy consumption (Yoo and Lee, 2010;  
81 You, 2013).

82 (2) *Industrial structure*. There are significant differences in the energy consumed by industries. Especially,  
83 heavy industry is a primary consumer. It is commonly viewed that industrialization increases energy  
84 consumption (Sadorsky, 2014). However, Li and Lin (2015) find negative effects for both middle-/low-  
85 income and high-income groups. This suggests that the change in industrial structure caused by  
86 development would affect the pattern of energy use.

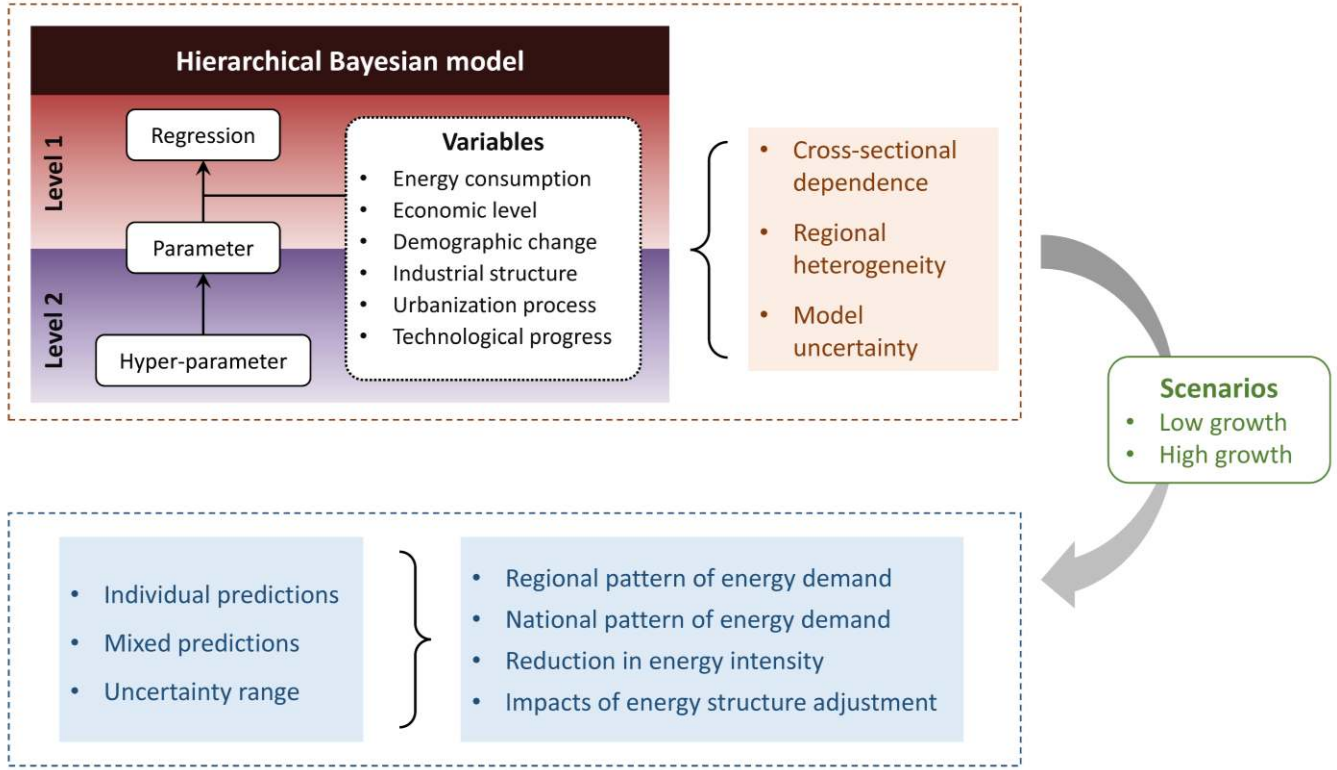
87 (3) *Demographic change*. The demographic factor (e.g. population and age structure) is an essential role  
88 considered for energy use in the literature (Liddle, 2014). Liu et al. (2015) find that the negative effect of

89 population density on energy consumption vary across regions of China. The given interpretation is the  
90 result of modernization.

91 (4) *Urbanization process*. The inconsistent findings exist in the historical studies (Al-mulali et al., 2012;  
92 York, 2007). Poumanyong and Kaneko (2010) show that urbanization decreases energy use in the low-  
93 income group, while it increases energy use in the middle- and high-income groups. The reduction is  
94 interpreted as the effects of fuel switching from inefficient traditional fuels to efficient modern fuels.  
95 However, development raises the use of private and public infrastructure so that more energy resources  
96 are required to support urban population and urban economies.

97 (5) *Technological progress*. The advancement of technology has impacts on energy efficiency and energy  
98 structure. These are essential for energy consumption. To cope with climate change, there is a need of new  
99 technologies to change the pattern of energy use in the future.

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



108

109 **Figure 1** Research framework for forecasting regional energy demand in China

110 **2.2 Hierarchical Bayesian model**

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

115

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

116 where  $\mathbf{x}_{st} = (x_{1,st}, x_{2,st}, \dots, x_{J,st})$  is a set of  $J$  explanatory variables associated with energy consumption per  
 117 capita of province  $s$  ( $s=1,2,\dots,S^{(g)}$ ) in year  $t$ . The regression coefficients  $\boldsymbol{\beta}_s^{(g)} = (\beta_{1,s}, \beta_{2,s}, \dots, \beta_{J,s})$ , the  
 118 intercepts  $\boldsymbol{\alpha}_s^{(g)} = (\alpha_1, \alpha_2, \dots, \alpha_s)$  and the covariance matrix  $\Sigma_g$  for group  $g$  all need to be estimated. If there

119 are  $G$  groups in total, the coefficients for each province can be denoted by  $\boldsymbol{\beta}_{s'} = (\beta_{1,s'}, \beta_{2,s'}, \dots, \beta_{J,s'})$  with  
 120  $s' = 1, 2, \dots, (S^{(1)} + S^{(2)} + \dots + S^{(G)})$ . To describe the spread of covariate effects across all provinces, another  
 121 multivariate normal distribution is applied to the regression coefficients. This indicates the second level  
 122 of the hierarchical Bayesian model, and the equation is shown as follows (Chen et al., 2014; Devineni et  
 123 al., 2013).

$$124 \quad \boldsymbol{\beta}_{s'} \sim \text{MVN}(\boldsymbol{\mu}_\beta, \boldsymbol{\Sigma}_\beta) \quad (2)$$

125 where  $\boldsymbol{\mu}_\beta$  (a vector of length  $J+1$ ) represents the common mean regression coefficients for all the provinces  
 126 from  $G$  groups; correspondingly,  $\boldsymbol{\Sigma}_\beta$  is the covariance matrix. If the estimated variances of  $\boldsymbol{\beta}_{s'}$  (diagonal  
 127 of  $\boldsymbol{\Sigma}_\beta$ ) are large, then it tends towards a no-pooling model where each province is regressed independently;  
 128 by contrast, the small variances imply a full pooling model with homogeneous responses to the influencing  
 129 factors (Gelman and Hill, 2007). We apply uninformative priors to the parameters  $\boldsymbol{\Sigma}_g$ ,  $\boldsymbol{\alpha}_\beta$ ,  $\boldsymbol{\mu}_\beta$ , and  $\boldsymbol{\Sigma}_\beta$ , and  
 130 use Markov Chain Monte Carlo (MCMC) sampling to estimate posterior distributions. The convergence  
 131 of the MCMC chain is evaluated by the potential scale reduction factor (Gelman and Rubin, 1992), and  
 132 all the calculations are conducted by R and RStan (Stan Development Team, 2016).

133 Considering the effects of economic development, industrialization, and urbanization, the explanatory  
 134 variables in Eq. (1) are selected as gross domestic product per capita, share of secondary industry, and  
 135 urbanization rate (the share of urban population in the total population). In addition, the quadratic term of  
 136 GDP per capita is introduced into the model to detect the nonlinear relationship between energy  
 137 consumption and economic development. Also, the lagged energy consumption per capita is involved to  
 138 establish dynamic models.

### 139 **2.3 Model validation**

140 Since our object is to extrapolate energy demand in the future, it is important to validate the models' out-  
 141 of-sample forecast performance. Accordingly, motivated by the typical leave-one-out cross-validation  
 142 (LOOCV) (James et al., 2013), we use the following root mean squared error (RMSE) criterion to measure  
 143 the out-of-sample performance of energy demand forecasting models considered in this study:



144

$$\text{RMSE} = \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{\sum_{i=1}^n (\hat{y}_{it} - y_{it})^2}{n}} \quad (3)$$

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where  $T$  and  $n$  are the numbers of years and provinces respectively.  $y_{it}$  ( $i=1,2,\dots,n$ ) is the actual energy consumption of the  $i$ th province in the  $t$ th year, while  $\hat{y}_{it}$  is its corresponding forecast which is obtained from the following procedure: hold out the observations of all studied provinces in the  $t$ th year (i.e.  $y_{1t}, y_{2t}, K, y_{nt}$ ) at first; then re-estimate the model on the remaining observations; finally, use this estimated model to obtain the required forecasts  $\hat{y}_{1t}, \hat{y}_{2t}, K, \hat{y}_{nt}$ . Clearly, this error can be reasonably used as a measure for the out-of-sample forecast performance. The smaller error indicates higher forecast accuracy.

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## 2.4 Data and scenarios

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### 2.4.1 Data description

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This study takes 30 provinces (including municipalities and autonomous regions) of China as a study area, and they are divided into three groups (Table A1). The annual data of provinces during 1995-2012 are collected from China Statistical Yearbooks, provincial Statistical Yearbooks, and China Energy Statistical Yearbooks, including GDP, population, urbanization rate, energy consumption, and share of secondary industry. Note that GDP is converted into 2010 price (Chinese Yuan, CNY). Table 2 presents the variables used for models and their descriptive statistics, and all the observations are taken for our analysis.

160

**Table 2** Variables for models and descriptive statistics

Variable	Definition	Observations	Mean	Std. dev.	Min	Max
GDPPC	GDP per capita (2010 CNY, thousands)	540	19.69	15.53	2.91	86.50
SEC	Share of secondary industry (%)	540	0.46	0.08	0.20	0.62
URB	Urbanization rate (%)	240	0.50	0.14	0.27	0.89
ENGP	Energy consumption per capita (tons of SCE)	540	2.16	1.32	0.42	7.95

161

162 **2.4.2 Scenario assumptions**

163 The projections of provincial GDP, population, urbanization rate, and share of secondary industry by 2030  
 164 are made based on the national projections from previous studies and some assumptions. Table 3 shows  
 165 the national projections in some specific years, and basically there are two scenarios designed to describe  
 166 the possible development. This paper intends to present the full range of energy demand, so the low and  
 167 high growth scenarios are adopted. The details for developing provincial scenarios are introduced as  
 168 follows.

169 **Table 3** Scenario assumptions for China

	S1 (low growth)			S2 (high growth)		
	2020	2025	2030	2020	2025	2030
GDP (trillions CNY)	90.4	118.1	147.2	92.6	123.9	158.1
Population <sup>a</sup> (millions)	1390.5	1385.6	1367.3	1415.2	1444.2	1463.8
Share of secondary industry (%)	38.9	35.7	32.6 <sup>b</sup>	39.8	37.4	35.0
Urbanization rate (%)	58.6	61.8	65.0	61.0 <sup>c</sup>	65.4 <sup>c</sup>	68.7 <sup>c</sup>

170 Sources: a. World Population Prospects: The 2015 Revision (United Nations, 2015)

171 b. China 2030 (Hu et al., 2014)

172 c. World Urbanization Prospects: The 2014 Revision (United Nations, 2014)

173

174 The GDP growth rates for the whole country in these scenarios refer to those in the World Energy Outlook  
 175 (2015). Specifically, the growth rate for scenario S1 (S2) is 6.0% (6.5%) in 2015-2020, 5.5% (6.0%) in  
 176 2021-2025, and 4.5% (5.0%) in 2026-2030. The structure of provinces' growth rate is assumed to be the  
 177 same as that in 2014. Accordingly, the future annual GDP of provinces are obtained.

178 There are small changes in the share of provincial population in the national population over the past years,  
 179 and thus the one in 2014 is taken to allocate the national population.

180 The smaller reduction in the share of secondary industry is made in scenario S2. On the basis of the  
 181 assumed values in Table 3, the annual national projections are linearly interpolated. Furthermore, the  
 182 structure of provinces' share of secondary industry in 2014 is taken to obtain annual provincial projections.

183 A comparatively small increase in urbanization rate is set in scenario S1. We linearly interpolate the values  
184 over the period to get annual urbanization rate of China. The share of provincial urban population in the  
185 national urban population was stable over the past years, and thus the one in 2014 is taken to calculate  
186 each province's projections of urbanization rate.

## 187 **3 RESULTS**

### 188 **3.1 Empirical models for energy demand**

189 The static and dynamic models for energy demand are established with various explanatory variables. The  
190 results estimated by fixed effects method and hierarchical Bayesian method are both made to reveal their  
191 differences. Note that the province fixed effects are only considered in the fixed effects estimation, and  
192 the common mean coefficients for all provinces in the hierarchical Bayesian model are taken for  
193 comparisons. The coefficient whose 90% interval of posterior distribution does not overlap with 0 is  
194 regarded to have significant effect.

195 The estimated regression coefficients of static models are shown in Table 4. The share of secondary  
196 industry is considered in all the models, and the significant positive impacts are found in model M1 by  
197 both fixed effects method and hierarchical Bayesian method. Urbanization rate is introduced into model  
198 M2 and M3, and the results suggest that energy consumption would increase with urbanization effect.  
199 However, the regression coefficients are not statistically significant. It also reveals that economic  
200 development would raise energy use, and particularly a significant nonlinear effect is indicated by two  
201 methods in model M3. Note that there are different situations for the provinces. Figure B1 displays the  
202 posterior distributions of the regression coefficients for each province in model M3. We notice that most  
203 provinces have significant nonlinear relationship between energy consumption and economic  
204 development. This implies that the energy demand is expected to decrease with further economic  
205 development, and the turning point varies from region to region. On the other hand, a time trend (TIME)  
206 is put into the models to represent technological effect. The significantly negative coefficients suggest that  
207 energy consumption would decrease with time.

208 The estimated regression coefficients of dynamic models are given in Table 5. In general, the current  
209 energy consumption is positively correlated to that in a former period. Yet, the insignificant coefficient is  
210 found by hierarchical Bayesian method in model M6. Also, it shows that industrialization and urbanization

211 have positive impacts on energy consumption, though the regression coefficients estimated by two  
 212 methods are not always statistically significant. In addition, model M6 attempts to investigate the  
 213 nonlinear effect of economic development. But Figure B2 shows that there is no significant relationship.  
 214 We notice that the regression coefficients of time trend estimated by two methods in model M4 are  
 215 contrary to each other. Specifically, the positive rather than negative impact of time trend is indicated by  
 216 fixed effect method.

217 **Table 4** The estimated regression coefficients of static models

	M1		M2		M3	
	FE	HB	FE	HB	FE	HB
Ln(GDPPC )	0.816*** (0.070)	1.091 [0.928, 1.289]	0.892*** (0.058)	1.054 [0.984, 1.134]	1.036*** (0.083)	1.176 [1.046, 1.308]
SEC	1.489*** (0.169)	0.258 [0.030, 0.508]	0.226** (0.105)	0.091 [-0.013, 0.193]	0.166 (0.106)	0.076 [-0.026, 0.186]
URB			0.280 (0.211)	0.179 [-0.015, 0.374]	0.250 (0.209)	0.194 [-0.004, 0.384]
Ln(GDPPC) <sup>2</sup>					-0.026** (0.011)	-0.019 [-0.039, -0.002]
TIME	-0.016** (0.007)	-0.040 [-0.062, -0.021]	-0.035*** (0.006)	-0.054 [-0.063, -0.046]	-0.032*** (0.006)	-0.054 [-0.062, -0.045]
RMSE	0.117	0.080	0.030	0.026	0.030	0.024
Observations	540	540	240	240	240	240

218 Note: FE indicates the fixed effects method while HB indicates the hierarchical Bayesian method. The medians of  
 219 common mean regression coefficients and the associated 5-95% uncertainty bounds (in square brackets) of HB  
 220 model are presented. The standard errors are given in the parentheses for the regression coefficients of FE model.

221 \* indicates significance at 10% level

222 \*\* indicates significance at 5% level

223 \*\*\* indicates significance at 1% level

224

225 The RMSE of model forecasts is calculated in Table 4 and Table 5 for comparison. It can be found that  
 226 all the models estimated by hierarchical Bayesian method have smaller RMSE which means better forecast  
 227 performances. This is partially because the region-specific coefficients (Figure B1 and B2) are provided  
 228 by hierarchical Bayesian method. These are essential for estimating future energy demand which needs to  
 229 fully account for regional heterogeneity. Besides, the cross-sectional dependence is also introduced into

230 the models which could improve estimation. Our study finally intends to give informative results of energy  
 231 demand, accordingly, we retain the variables of insignificant effects since they can still provide some  
 232 information for the posterior distribution of energy demand.

233 **Table 5** The estimated regression coefficients of dynamic models

	M4		M5		M6	
	FE	HB	FE	HB	FE	HB
Ln(GDPPC)	0.085* (0.047)	0.521 [0.403, 0.642]	0.596*** (0.066)	1.030 [0.932, 1.120]	0.738*** (0.084)	1.121 [0.984, 1.275]
SEC	0.671*** (0.100)	0.258 [0.061, 0.472]	0.119 (0.094)	0.090 [-0.025, 0.194]	0.059 (0.095)	0.078 [-0.029, 0.182]
URB			0.102 (0.189)	0.156 [-0.053, 0.369]	0.073 (0.187)	0.175 [-0.035, 0.377]
Ln(ENGP(-1))	0.749*** (0.025)	0.523 [0.436, 0.606]	0.358*** (0.049)	0.043 [0.000, 0.089]	0.358*** (0.048)	0.035 [-0.008, 0.083]
Ln(GDPPC) <sup>2</sup>					-0.026*** (0.010)	-0.016 [-0.036, 0.002]
TIME	0.011*** (0.004)	-0.017 [-0.026, -0.007]	-0.026*** (0.005)	-0.054 [-0.063, -0.044]	-0.024*** (0.005)	-0.052 [-0.061, -0.043]
RMSE	0.063	0.061	0.029	0.026	0.028	0.025
Observations	510	510	210	210	210	210

234 Note: FE indicates fixed effects method while HB indicates hierarchical Bayesian method. The medians of common  
 235 mean regression coefficients and the associated 5-95% uncertainty bounds (in square brackets) of HB model are  
 236 presented. The standard errors are given in the parentheses for the regression coefficients of FE model.

237 \* indicates significance at 10% level

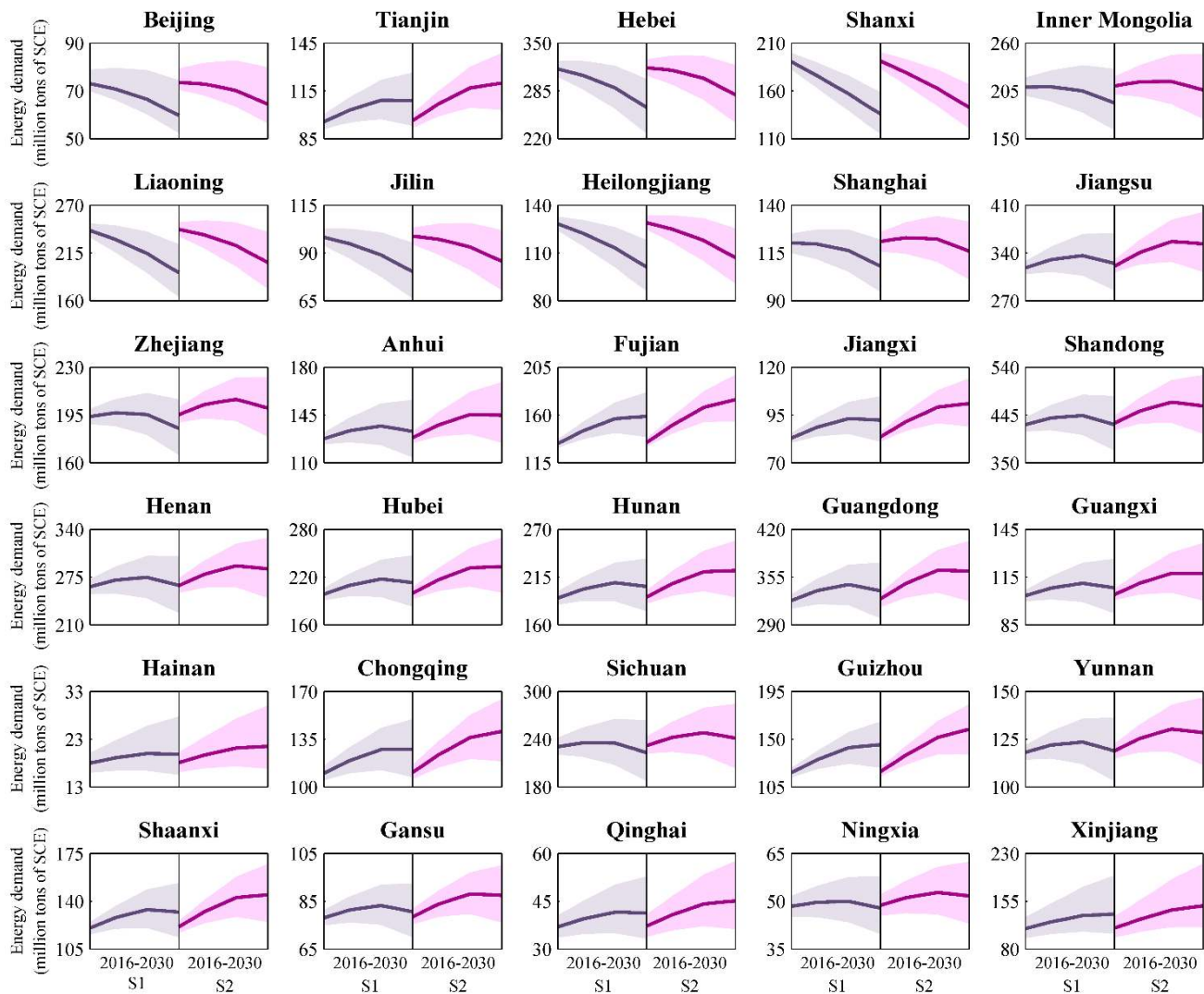
238 \*\* indicates significance at 5% level

239 \*\*\* indicates significance at 1% level

240

### 241 3.2 Forecasting regional energy demand by 2030

242 The posterior distributions of energy demand estimated by the models (M2, M3, M5, and M6) reflecting  
 243 the integrated effects of economic development, industrialization, and urbanization are adopted. Then,  
 244 these are mixed to present the probabilistic forecasts. The provincial energy demand with uncertainty  
 245 bound during 2016-2030 is presented in Figure 2. There are different situations across provinces due to  
 246 the various development stages.



247

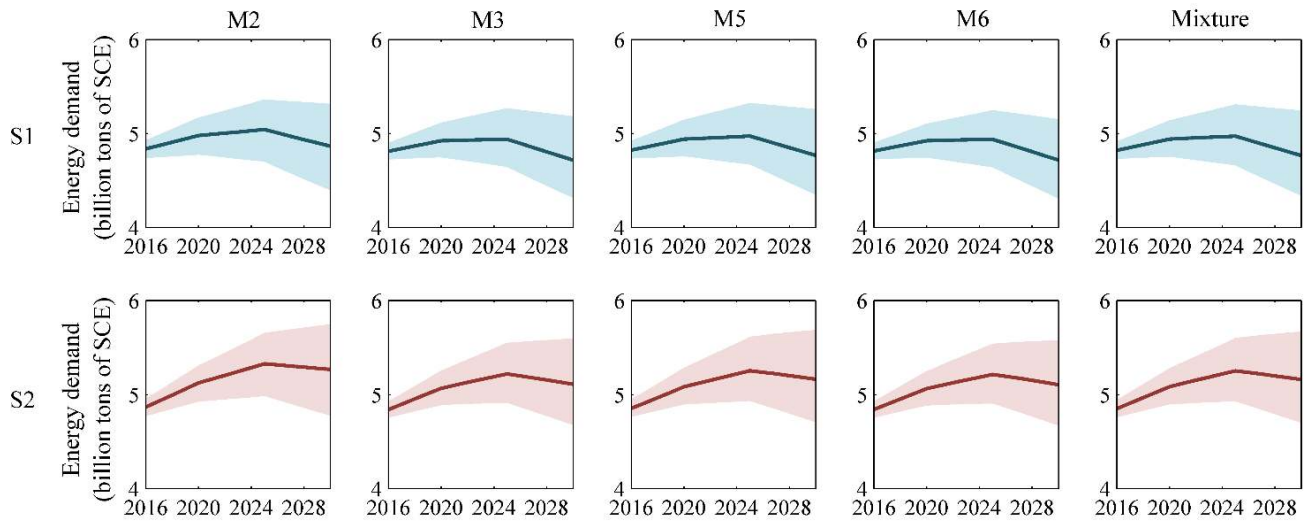
248 **Figure 2** Provincial energy demand during 2016-2030 in scenario S1 and S2. The lines indicate median  
 249 value while the range indicates 2.5-97.5% uncertainty.

250 The ongoing economic transformation in China makes slower economic development in Hebei,  
 251 Heilongjiang, Jilin, Liaoning and Shanxi, so that the desire for energy is expected to continuously decrease  
 252 in the future. From 2016 levels by 2030, the amount of energy use (median value) in scenario S1/S2 would  
 253 reduce by 16.6%/11.6% in Hebei, 21.1%/17.0% in Heilongjiang, 18.3%/13.2% in Jilin, 20.1%/15.7% in  
 254 Liaoning, and 28.6%/25.4% in Shanxi. Also, there are significant reductions in Beijing, Inner Mongolia,  
 255 and Shanghai.



274 **3.3 Forecasting national energy demand by 2030**

275 Based on the provincial estimates, the national energy demand and the associated uncertainty bound are  
 276 shown in Figure 4. Here, the distributions predicted by the selected individual models and the mixture of  
 277 distributions are all presented for comparison. Basically, these individual models indicate that the total  
 278 energy demand (median value) could reach the peak in the scenarios. Specifically, model M2 suggests  
 279 higher demand (median value) than other models, reaching 5.04/5.33 billion tons of SCE by 2025 in  
 280 scenario S1/S2. Comparatively, the smaller peak (median value) of 4.94/5.21 billion tons of SCE in  
 281 scenario S1/S2 is found by model M6. By aggregating the predicted distributions of all individual models,  
 282 the mixed distribution shows that the maximum demand (median value) could rise to 4.97/5.25 billion  
 283 tons of SCE in scenario S1/S2. However, the upper uncertainty bounds in scenario S2 suggest that the  
 284 energy demand would keep growing. The mixed predictions show that it could be as much as 5.67 billion  
 285 tons of SCE in 2030.



286

287 **Figure 4** National energy demand predicted in scenario S1 and S2 by individual models (M2, M3, M5  
 288 and M6) and the mixed predictions. The line indicates median value while the range indicates 2.5-97.5%  
 289 uncertainty.

290 We also attempt to investigate the changes in energy demand with a focus on the effect of economic  
 291 development. Accordingly, three economic development scenarios (Table 6) are established. For the  
 292 prediction, other variables such as population, urbanization rate, and share of secondary industry are all  
 293 consistent with those in scenario S1. The growth rates of GDP in the medium and low economic growth



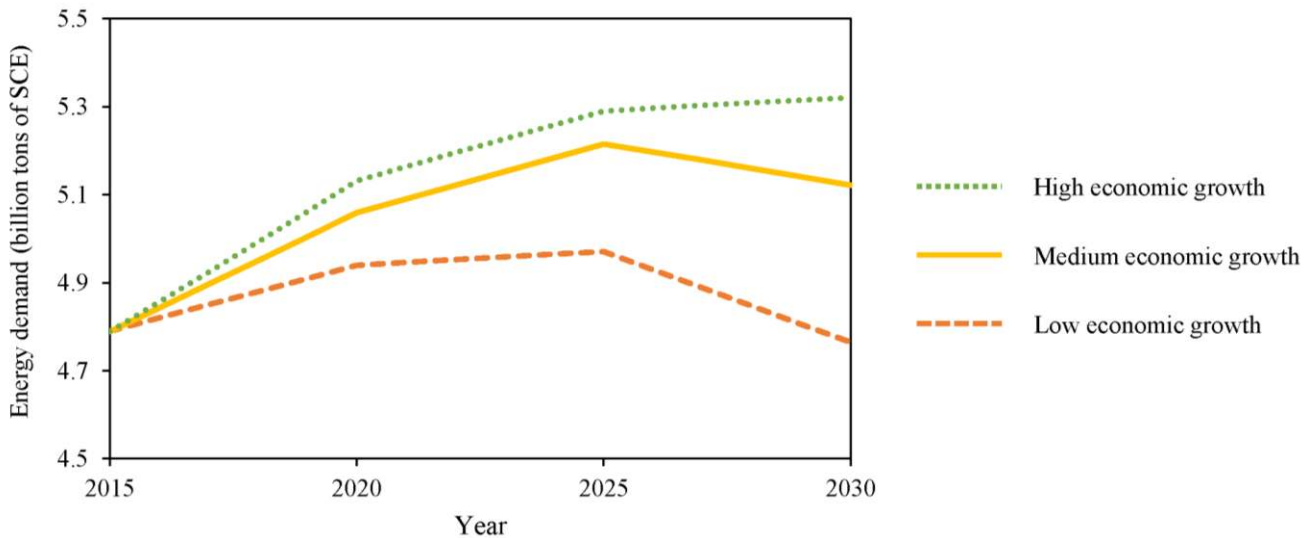
294 scenarios are the same as those in scenario S2 and S1. Since the government aims to make the average  
 295 GDP growth higher than 6.5% during the 13<sup>th</sup> Five-Year Plan of China (2016-2020), we set the growth  
 296 rate as 6.8% in the high economic growth scenario. Besides, the slower economic decline is also assumed  
 297 during 2026-2030 for the high economic growth scenario. As shown in Figure 5, the energy demand  
 298 (median value) would increase to 5.21 and 4.97 billion tons of SCE in the medium and low economic  
 299 growth scenarios, respectively, and decrease to 5.12 and 4.76 billion tons of SCE by 2030. However, the  
 300 energy demand (median value) in the high economic growth scenario is likely to increase continuously to  
 301 5.32 billion tons of SCE.

302 **Table 6** Scenario assumptions for GDP growth rate

Scenario	2016-2020	2021-2025	2026-2030
High economic growth	6.8%	6.0%	5.5%
Medium economic growth	6.5%	6.0%	5.0%
Low economic growth	6.0%	5.5%	4.5%

303 Note: other variables in the three scenarios are the same as those in scenario S1.

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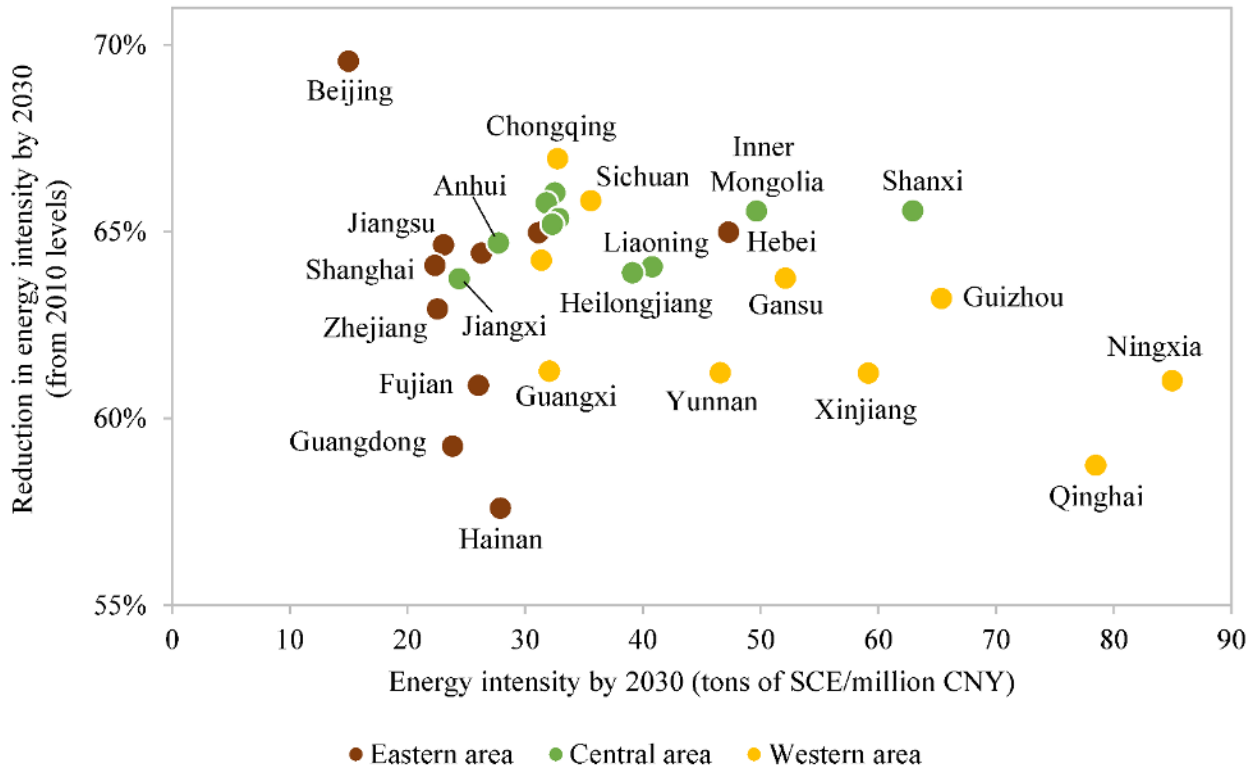


305

306 **Figure 5** Energy demand (median value) in three scenarios of different economic development

307 **3.4 Energy intensity reduction**

308 Energy intensity (the amount of energy consumed by per unit of GDP) is a key indicator in China’s energy  
 309 planning. The smaller value suggests better energy efficiency of economy. According to the mixed  
 310 predictions, the changes in energy intensity (median value) are calculated. Figure 6 presents the regional  
 311 energy intensity by 2030 and the associated reductions from 2010 levels in scenario S1.



312

313 **Figure 6** Energy intensity (median value) by 2030 and the associated reductions from 2010 levels in  
 314 scenario S1

315 The eastern provinces have lower energy intensity by 2030 that is 26.6 tons of SCE per million CNY on  
 316 average. The amount of energy consumed by per unit GDP in Beijing by 2030 is 15.0 tons of SCE per  
 317 million CNY, the smallest among all the provinces. By comparison, the western provinces have higher  
 318 mean energy intensity of 51.8 tons of SCE per million CNY. In particular, the largest value of 85.0 tons  
 319 of SCE per million CNY is found in Ningxia. Generally, economic development in the provinces of more  
 320 energy-intensive industries such as Gansu, Guizhou, Inner Mongolia, Ningxia, Qinghai, Shanxi, and  
 321 Xinjiang would consume more energy. Most of them are less developed in the central and western areas,

322 and thus it is necessary to help them adjust industrial structure. Yet, the developed provinces in the eastern  
323 area such as Beijing, Guangdong, Jiangsu, Shanghai, and Zhejiang have advanced technology to make  
324 energy intensity lower.

325 On the other hand, there are different performances in energy intensity reduction across provinces. The  
326 central provinces decrease by 65.0% on average, and they seem to have similar changes. In contrast, the  
327 eastern provinces vary greatly in the reductions in energy intensity. Specifically, Beijing would decrease  
328 by 69.6%, larger than other provinces. Yet, the smallest reduction of 57.6% is found in Hainan. In addition,  
329 Chongqing and Sichuan would make bigger improvements in energy efficiency than other western  
330 provinces.

### 331 **3.5 Impacts of energy structure adjustment**

332 Energy structure adjustment becomes essential for carbon dioxide emissions reduction. On the basis of  
333 the mixed primary energy demand predictions, we attempt to investigate whether the proposed emissions  
334 reduction targets can be achieved. Accordingly, the energy structure in 2020 and 2030 (Table 7) provided  
335 by Hao et al. (2016) is used for our analysis.

336 The carbon emissions are calculated based on the coefficients given by Zhu et al. (2015). By 2020, the  
337 carbon intensity (carbon dioxide emissions per unit of GDP) would decrease by 55.6-58.9% in scenario  
338 S2 and 55.8-59.1% in scenario S1 from 2005 levels. Meanwhile, the reductions in carbon intensity would  
339 reach 74.5-78.9% in scenario S2 and 74.7-79.1% in scenario S1 by 2030. This implies that the current  
340 reduction targets could be realized with the energy structure adjustment. On the other hand, the carbon  
341 dioxide emissions peak would appear before 2030 since the decreases in energy demand.

342 The shares of non-fossil energy in Table 7 are close to the expected goals in China's energy plans. As a  
343 result, it can be obtained that the non-fossil energy demand (median value) by 2020 and 2030 is as much  
344 as 0.74/0.76 and 1.00/1.08 billion tons of SCE in scenario S1/S2, respectively. We notice that the  
345 increment in non-fossil energy consumption during 2010-2015 was 0.19 billion tons of SCE, and the non-  
346 fossil energy consumption in 2015 was 0.59 billion tons of SCE. This means that future development of  
347 non-fossil energy can roughly achieve the goal by 2020.

348

349 **Table 7** China’s energy structure in 2020 and 2030

	Coal	Oil	Natural gas	Non-fossil energy
2020	57.3%	17.6%	10.1%	15.0%
2030	50.3%	16.8%	11.9%	21.0%

350 Source: Hao et al. (2016)

351 **4 DISCUSSION**

352 Recent studies have also investigated China’s future energy demand using different methods and data  
 353 (Table 8). By comparison, the regional analysis can gather more information to give more specific insights  
 354 for energy planning. As argued by the literature, the analysis with a focus on a panel of different regions  
 355 needs to account for heterogeneity and cross-sectional dependence. It is improper to assume that the  
 356 impacts on energy consumption are homogeneous across regions due to the varying development stages.  
 357 Meanwhile, a relation of energy consumption between two regions may naturally exist, especially for  
 358 those in similar geographical, economic, and political conditions. These issues are addressed in this study  
 359 by hierarchical Bayesian approach. Furthermore, the distribution of the projected energy demand is  
 360 presented to provide detailed information. It should also be noticed that the Bayesian approach can  
 361 incorporate prior information to improve estimates. This requires the specific knowledge of the effect of  
 362 influence factor.

363 **Table 8** China’s energy demand projected by the literature and this study (billion tons of SCE)

Source	Data level	Energy demand in 2030 (low value)
Lin and Ouyang (2014)	Provincial	5.59
Wu and Peng (2017)	National	4.60
This study	Provincial	4.76 (4.34-5.24)

364 Note: this study gives the median and the 2.5-97.5% range in the parentheses.

365 Although various scenarios are assumed, our low estimate of China’s energy demand in 2030 is close to  
 366 those in the literature (Table 8). Besides, this study shows that the energy demand peak would reach 5.25  
 367 (median value) billion tons of SCE in the high growth scenario. This is approximate to the amount of 5.30  
 368 billion tons of SCE given by Wu et al. (2017). As a result, the projections in this study are reasonable.

369 We find that there is no obvious energy demand peak in most western provinces. The unbalanced regional  
370 development in China makes the possible rapid economic growth in western area in the future, and thus  
371 the desire for energy might keep growing. It needs to be cautious to make plans for controlling energy use,  
372 since there might be a restriction on regional economy. Our analysis shows that most western provinces  
373 still have great potential for energy intensity reduction, and the advanced technology adoption and  
374 industrial structure adjustment are effective measures (Mi et al., 2015). Especially for Guizhou and  
375 Qinghai, their energy intensity is higher with the increased energy use. The energy-intensive industries  
376 should be cut down to improve energy efficiency.

377 Energy structure adjustment is still a critical issue in China's energy planning. The results suggest that  
378 China's new normal of economy might maintain the increase in national energy demand. Besides, current  
379 population policy may delay the decrease in national population, and further urbanization process could  
380 raise energy demand. In that case, energy structure adjustment is essential for reducing carbon dioxide  
381 emissions. Specifically, it needs to further decrease coal consumption but increase renewable energy (Li  
382 et al., 2017). The western provinces have abundant resources of renewable energy. Therefore, the  
383 development of renewable energy could promote industry in this region.

## 384 **5 CONCLUSIONS**

385 This study investigates the ranges of China's future energy demand accounting for sub-national  
386 heterogeneity, cross-sectional dependence, and quantification of uncertainty, and offers a predictive  
387 distribution of energy demand. The following primary conclusions are drawn from our analysis.

388 (1) The hierarchical Bayesian approach partially pools the common information from different regions  
389 and provides region-specific regression coefficients and associated uncertainty with flexibly  
390 modeling the dependence between variables. It indicates that the hierarchical Bayesian approach has  
391 better performance in model fitting than the fixed effect method. The probabilistic forecasts are  
392 informative and of great importance for energy policy making.

393 (2) The eastern and central areas could peak their energy demand in the scenarios designed by this study.  
394 However, the western area would keep energy demand growing to 1.27 billion tons of SCE by 2030  
395 in the high growth scenario. As for the whole country, the mixed predictions show that the maximum  
396 demand could rise to 4.97/5.25 billion tons of SCE in the low/high growth scenario.

397 (3) The economic development in the provinces of more energy-intensive industries such as Gansu,  
398 Guizhou, Inner Mongolia, Ningxia, Qinghai, Shanxi, and Xinjiang would consume more energy. Yet,  
399 the developed provinces in the eastern area such as Beijing, Guangdong, Jiangsu, Shanghai, and  
400 Zhejiang would have lower energy intensity. On the other hand, the central provinces could decrease  
401 energy intensity by 65.0% on average, and they seem to have similar changes. In contrast, the eastern  
402 provinces vary greatly in the reductions in energy intensity. In addition, Chongqing and Sichuan  
403 would make bigger improvements in energy efficiency than other western provinces.

404 (4) By 2020, the carbon intensity would decrease by 55.6-58.9% in scenario S2 and 55.8-59.1% in  
405 scenario S1 from 2005 levels. Meanwhile, the reductions in carbon intensity would reach 74.5-78.9%  
406 in scenario S2 and 74.7-79.1% in scenario S1 by 2030. Moreover, the non-fossil energy demand  
407 (median value) by 2020 and 2030 is as much as 0.74/0.76 and 1.00/1.08 billion tons of SCE in scenario  
408 S1/S2, respectively.

409 There are still large uncertainties in future socioeconomic development. Further work should give more  
410 information to improve projection, such as scenario design and parameter setting. The Bayesian  
411 framework could actually integrate all the uncertainties and provide a more informative estimate of energy  
412 demand.

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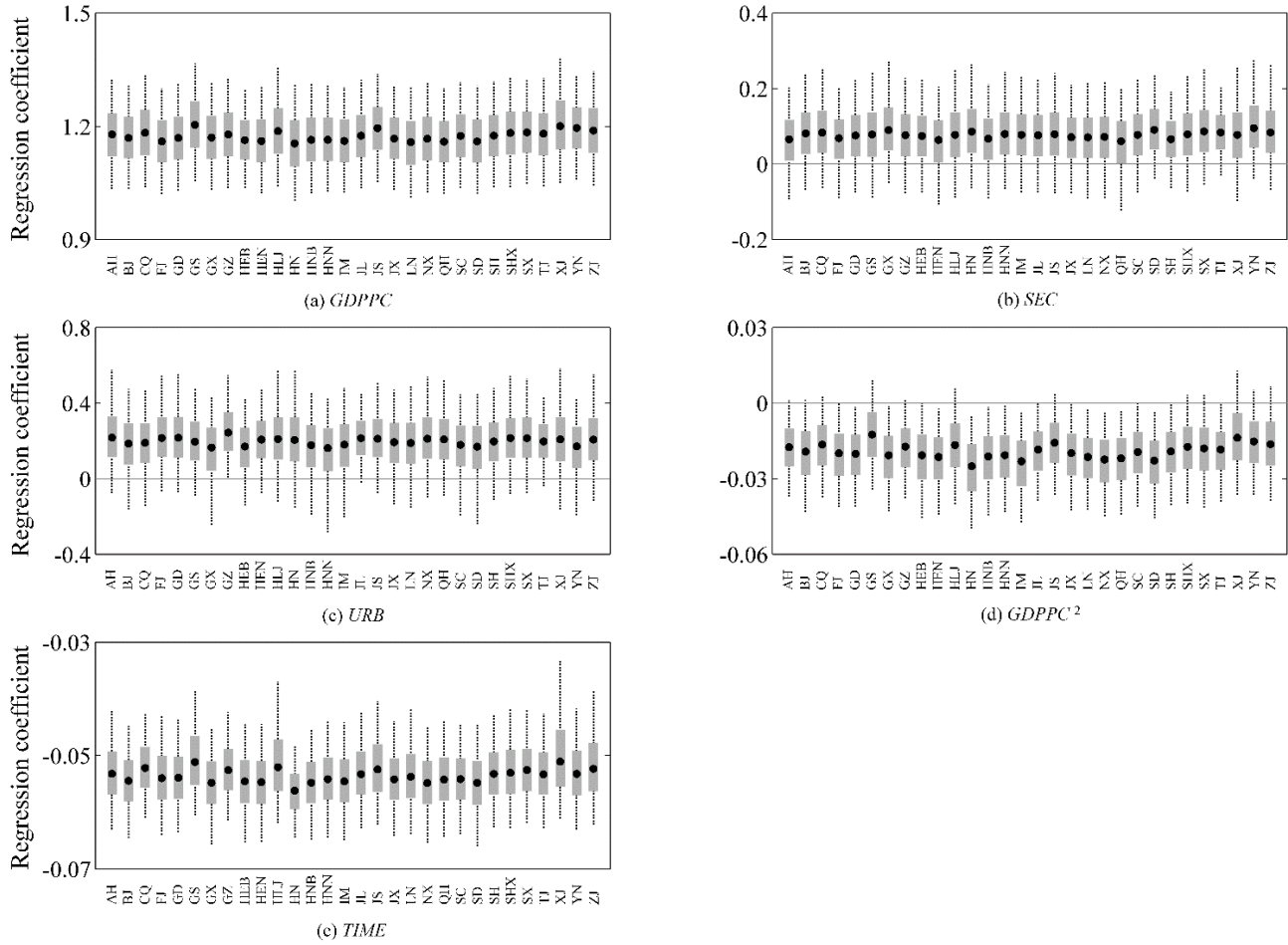
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423 **APPENDIX A**424 **Table A1** Abbreviations for China's provinces in three areas

Eastern area		Central area		Western area	
Beijing	BJ	Anhui	AH	Chongqing	CQ
Fujian	FJ	Henan	HEN	Gansu	GS
Guangdong	GD	Heilongjiang	HLJ	Guangxi	GX
Hebei	HEB	Hubei	HUB	Guizhou	GZ
Hainan	HN	Hunan	HUN	Ningxia	NX
Liaoning	LN	Inner Mongolia	IM	Qinghai	QH
Jiangsu	JS	Jilin	JL	Sichuan	SC
Shandong	SD	Jiangxi	JX	Shaanxi	SHX
Shanghai	SH	Shanxi	SX	Xinjiang	XJ
Tianjin	TJ			Yunnan	YN
Zhejiang	ZJ				

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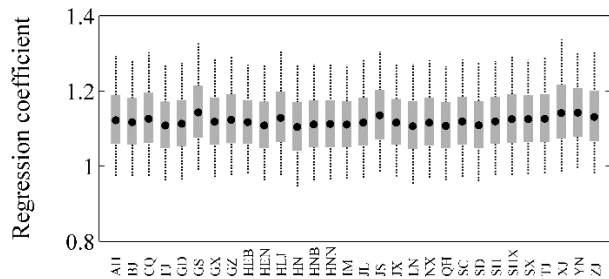
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428 **Figure B1** Regression coefficients and the associated uncertainty bounds for model M3. Each box shows  
 429 the posterior distribution of the regression coefficient of a province with the 25<sup>th</sup>, median, and 75<sup>th</sup>  
 430 percentile, and whiskers extend to the 5<sup>th</sup> and 95<sup>th</sup> percentile.

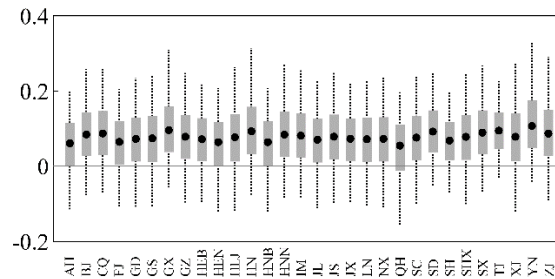
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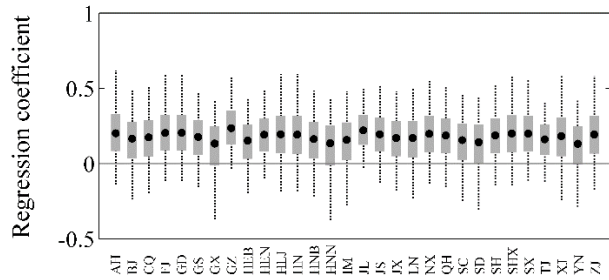




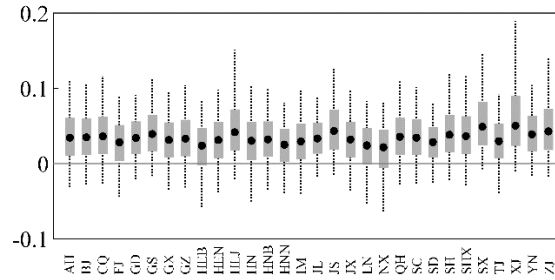
(a) *GDPPC*



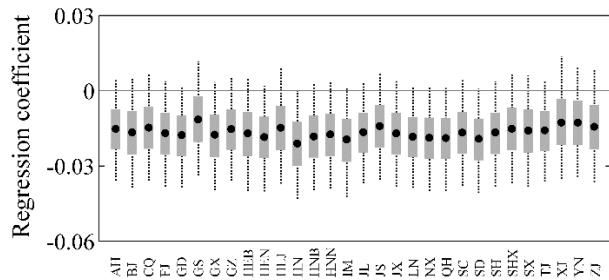
(b) *SEC*



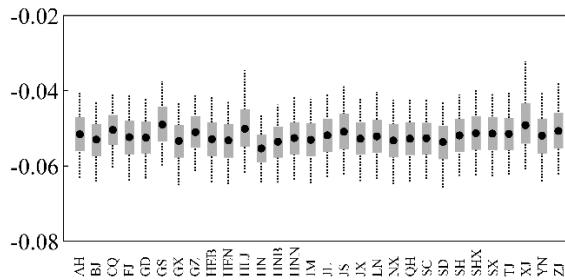
(c) *URB*



(d) *ENG(-1)*



(e) *GDPCC<sup>2</sup>*



(f) *TIME*

433

434 **Figure B2** Regression coefficients and the associated uncertainty bounds for model M6. Each box shows  
 435 the posterior distribution of the regression coefficient of a province with the 25<sup>th</sup>, median, and 75<sup>th</sup>  
 436 percentile, and whiskers extend to the 5<sup>th</sup> and 95<sup>th</sup> percentile.

437

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