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China's challenge for decarbonized growth: Forecasts from energy demand models

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Abstract

This paper employs a spatial dynamic panel model to forecast China's energy consumption in 2011–2020. We find that energy consumption would continue to increase at least till 2020, with annual growth rates of 10% in 2011–2015 and 6% in 2016–2020. A higher proportion of service sectors in the economy and technological progress reduce energy demand. However, the latter appears to have dwindled impact since 2001. Strong spatial dependence implies copying behaviour in energy consumption across regions. Therefore, more efficient energy control at the disaggregated level can have multiplied impact on the country's goal in energy saving and carbon emission reducing.

JEL classification: C3; Q4

Keywords: Energy consumption; Spatial dependence; Dynamic panel; Forecasts; China

1. Introduction

Along with more than 30-years economic prosperity, China has been increasingly demanding energy to fuel the remarkable growth (Fig. 1). China became a net energy importer in 1998 and the net import dependency soared from about 3% in 1998 to 7% in 2007.[1] The average annual

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[1] The net import dependency is the percentage share of net energy imports in total primary energy use. Data are available with the World Bank: http://data.worldbank.org/indicator/EG.IMP.CONS.ZS (accessed on 30 May 2011).

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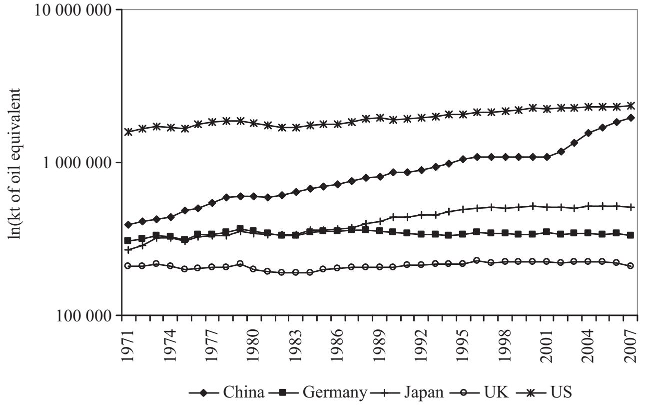

Fig. 1. Primary energy consumption, 1971–2007.
Source: International Energy Agency. Available at the World Bank: http://data.worldbank.org/indicator/EG.USE.COMM.KT.OE (accessed on 30 May 2011).

growth rate of primary energy consumption between 1971 and 2007 was 4.6%, while it was about 1% for the US in the same period. The most dramatic increase has been taking place since 2000 with 7.8% increase per annum. In comparison, the US experienced 0.7% of annual growth, while the UK and Germany even reduced the demand. Meanwhile, it has been long argued that China's energy use lacks efficiency.[2] Although the energy intensity in terms of energy use per $1000 GDP (constant 2005 PPP) dropped sharply by 75.7% between 1980 and 2007, the magnitude was still 1.6 times as much as US at the end of 2007 and ranked 25 out of 128 countries and regions.[3]

Note: Primary energy consumption refers to the use of primary energy before transformation to other end-use fuels, which is equal to indigenous production plus imports and stock changes, minus exports and fuels supplied to ships and aircraft engaged in international transport.

The rising energy demand and relatively high energy-intensive growth lead to massive greenhouse gas (GHG) emissions. The total CO_2 emissions in China have surpassed the US and ranked 1 since 2009 (IEA, 2010). It is increasingly expected that China will play a vital role in addressing climate change (IEA, 2010; Zhang, 2004). Hence it is important to study the trend of China's energy demand and its socio-economic determinants. This could benefit policy makers to adopt the appropriate energy strategic planning to mitigate climate change and promote sustainable development in the period of the government's 12th "Five-year Plan" (2011–2015) or a medium term.

The existing studies have widely investigated the relationship between energy needs (extended to pollution or GHG emissions) and economic growth in China. A number of efforts are devoted to test whether the relationship is indicative of an environmental Kuznets curve (EKC), which, however, could be bedevilled by regional heterogeneity. In addition, many examine the short or long run causality between energy use and economic growth by using VAR and VECM frameworks. In general, no conclusive evidence has been found. Lee and Chang (2008) and Chontanawat, Hunt, and Pierse (2008) identify the causality running from energy consumption to GDP. However, the

[2] The figures in this and last sentences are author's calculations based on data from International Energy Agency, which are available at the World Bank: http://data.worldbank.org/indicator/EG.USE.COMM.KT.OE (accessed on 30 May 2011).

[3] Data come from Millennium Development Goals Database, UN Statistics Division: http://data.un.org/Data.aspx?d=MDG&f=seriesRowID%3a648 (accessed on 30 May 2011).

causality is found to be sensitive to the specific period under investigation (Zou & Chau, 2006). Soytas and Sari (2006) show that the causality between the growth rates of energy demand and economic growth exists only in the short run, but would dissipate quickly after one period. The causality is also sensitive to specific varieties of energy in use (*e.g.*, oil in Zou & Chau, 2006) and different industries (*e.g.*, the secondary industry in He, Lao, Osuch, Zuo, & Wen, 2008).

Based on the estimated relationship between energy use and GDP, a growing body of literature forecasts China's future energy demand (Table 1). Different modelling strategies broadly support continuously growing needs for primary energy and therefore GHG emissions with varying magnitude in both the near and distant future.

Given all above, forecasts of China's energy use and CO_2 emissions are subject to two problems in the existing literature. First, most estimation is based on data at the national level, while there are only a few attempts to employ regional data (*e.g.*, Auffhammer & Carson, 2008; Cattaneo, Manera, & Scarpa, 2011). However, it is use of disaggregated information (Auffhammer & Steinhauser, 2007) and accounting for regional heterogeneity (Baltagi, Bresson, & Pirotte, 2009) that can dramatically improve the accuracy of forecasts. More importantly, the inter-dependence across regions is often neglected, while some recent studies do reveal increasing and strong spatial inter-province dependence in economic growth in China (Aroca, Guo, & Hewings, 2006; Girardin & Kholodilin, 2009; Ying, 2003). Correcting models for possible spatial interdependence can significantly improve forecasting performance (Auffhammer & Carson, 2008; Auffhammer & Steinhauser, 2007; Giacomini & Granger, 2004; Girardin & Kholodilin, 2009).

This paper offers more accurate forecasts of China's primary energy consumption by using disaggregated data at the provincial level and estimating spatial dynamic panel models taking both provincial heterogeneity and inter-dependence into account. It also contributes to the existing spatial energy studies for China by addressing the possible endogeneity of spatial lag dependence. Overall, the analysis points to a trend of increasing primary energy use for China at least till 2020, with an annual growth rate of 6.45–10%. There is no supporting evidence of an EKC between energy use and economic growth even after controlling for spatial effects. Provinces' energy consumption suggests strong copying behaviour. Under the inter-dependence of energy consumption across provinces, the government needs to pay more attention to regional energy-saving policy-making, which suggests amplified impact on the national energy conservation.

The present study proceeds as follows. The model set-up and the steps of forecasting are outlined in the next section. Section 3 describes the data. Estimation and forecasts are discussed in Section 4. Section 5 concludes.

2. Methodology

2.1. Modelling provincial energy demand

We adopt the model specification in Auffhammer and Carson (2008) to express provincial energy demand. The logarithmic per capita energy consumption, ln(PEC), for province i at time t takes the following reduced form:

$$\begin{aligned}\ln(\mathrm{PEC}_{it}) = \beta_0 + \beta_1\ \ln(\mathrm{PGDP}_{it}) + \beta_2\ \ln(\mathrm{PGDP}_{it})^2 + \beta_3\ \ln(\mathrm{PEC}_{i,t-1}) \\ + \beta_4 \sum_{j=1}^{k} w_{ij}\ \ln(\mathrm{PEC}_{j,t-1}) + x'_{it}\beta_5 + \alpha_i + \eta_t + u_{it} \qquad (1)\end{aligned}$$

Table 1
Summary of literature on forecasting China's CO_2 emissions and energy consumption.

Literature	Forecasting horizon	Projection (annual growth rate %)
CO_2 emissions		
Auffhammer and Carson (2008)	2006–2010	11.05–11.88
ERI (2004)	2000–2010	4.18
Fridley (2006)	2000–2010	5.00–5.02
IEA (2007)	2006–2030	4.94
IPCC (2000)	2000–2010	2.58–4.82
Jiang and Hu (2006)	2000–2010	4.12
Marland et al. (2007)	2000–2004	12.51
Onishi (2007)	2006–2010	7.3
	2011–2020	3.3
Van Vuuren, Zhou, De Vries, Jiang, and Graveland (2003)	2000–2050	2.0–2.6
Yang and Schneider (1998)	2000–2025	1.93–3.10
Energy consumption		
Adams and Shachmurove (2008)	2002–2020	Energy import: 2002–2010: 12.4 2010–2020: 13.8
Cattaneo et al. (2011)	2010	Industrial coal: 2
Crompton and Wu (2005)	2004–2010	3.8
Dong (2000)†	1996–2020	120.44
EIA (2011)†	2009–2035	118
Fan, Liu, Wu, Tsai, and Wei (2007)†	1997–2020	CO_2: 77.01–149.43 energy: 100–180.85
Hirschhausen and Andres (2000)†	1996–2010	Electricity: 121–148
IEA (2010)†	2008–2035	75
Kadoshin, Nishiyama, and Ito (2000)†	2005–2010	34.68
Liao, Fan, and Wei (2007)	1997–2020	Energy: 3.67–5.11 for the coast; 2.15–3.5 for the southwest
Ma et al. (2008)	2002–2010	0.61–1.76
McFarland, Paltsev, and Jacoby (2009)†	2000–2050	Coal: >200 in all scenarios

Note: †These growth rates are not annualized in the literature, but is defined as the total growth over the whole forecast horizon compared with the value in base year.

where $\ln(\text{PGDP}_{it})$ is the provincial real per capital GDP; w_{ij} denotes the spatial weight capturing interdependence across provinces; $\sum_{j=1}^{k} w_{ij} \ln(\text{PEC}_{j,t-1})$ represents spatial interactions of provincial energy use with j representing neighbour of province i; k is the total number of neighbours imposing spatial influence on the province i; x'_{it} includes all exogenous variables, such as urbanization, per capita ownership of cars and the provincial economic structure which will be discussed in detail in Section 3; α_i and η_t are province and time fixed effects respectively; u_{it} is the white noise error.

Including the second order polynomial of per capita GDP is to test for the hypothesis of EKC, namely an inverted U-relationship between energy consumption and the level of economic development. The presence of EKC is indicated by a negative $\hat{\beta}_1$ and a positive $\hat{\beta}_2$. In addition to per capita GDP, the current energy consumption in province i may also correlate with its past energy demand. In other words, energy consumption might suggest some time dependence, given the socioeconomic background. Such impact is reflected by $\hat{\beta}_3$.

One particular interest to us is the spatial influence from the neighbouring areas' energy consumption and hence the forecasts of aggregate energy demand at the national level. As Auffhammer and Carson (2008) suggested, we consider the spatial lag dependence in provincial energy consumption by including $\sum_{j=1}^{k} w_{ij} \ln(\text{PEC}_{j,t-1})$. This implies that the province i's current energy consumption is influenced by previous energy consumption of surrounding k provinces. For example, it might be the case that a relatively poor province is enticed by its affluent neighbour's path of industrialization to establish more industrial plants and therefore, to consume more energy and emit more GHG.[4] Taking these inter-province influences into account will improve the estimation (Franzese & Hays, 2007) as well as the forecast ability (Giacomini & Granger, 2004).

Before proceeding, it is useful to note that the estimates in a spatial model are very sensitive to the choice of spatial weights, since it makes *ad hoc* and *a priori* structure of cross-province interactions. These spatial weights define how the spatial dependence is delivered across provinces based on the geographic locations. The present paper constructs a distance-based spatial matrix $W_{28\times 28}$ with spatial elements being:

$$w_{ij} = \begin{cases} 1 & \text{if } j \in J \\ 0 & \text{if } j \notin J \end{cases}$$

where $i, j \in (1, 2, \ldots, 28)$ denote 28 provinces in our data; J includes the set of neighbours which are restricted to provinces with no more than 1000 miles from each other's capital city.[5] When $i = j$, w_{ij} equals zero (Anselin, 2001). $W_{28\times 28}$ is then row-normalized and fulfils all requirements stated by Giacomini and Granger (2004).[6] We let the sum of each row equal one, *i.e.* $\sum_j w_{ij} = 1$. This facilitates the comparison of estimated spatial dependence effect $\hat{\beta}_4$ across different spatial model specifications. By attaching $W_{28\times 28}$ to the lagged per capita energy consumption of province i's neighbours at time t, we actually assume that its current energy consumption is equally influenced by the surrounding provinces' lagged energy needs at $t-1$.

[4] For example, spatial inter-dependence has been found in European countries' sulphur emissions (Maddison, 2007) and provincial CO_2 emissions in China (Auffhammer and Carson, 2008).

[5] Ying (2003) finds that the spatial effect in China is most likely to exist between regions within 2000 km from each other.

[6] We also attempted a simple binary contiguity spatial weight matrix with elements being one if two provinces share borders, which is prevailing in many studies (Auffhammer and Carson, 2008; Cattaneo et al., 2011; Giacomini and Granger, 2004; Maddison, 2007). However, the exploratory spatial tests (global and local Moran's I) suggest that neither per capita energy consumption nor per capita GDP has spatial inter-dependence.

In the empirical analysis, we gradually include more independent variables into the regression to discuss specifically each variable and the robustness of our model specifications. Given that spatial lag energy consumption might be endogenous in Eq. (1), we use two-step GMM in the estimation to address this issue. The excluded instruments for the spatial lag energy consumption is the first and second spatial lags of log per capita real GDP.

2.2. Forecasting

Based on the estimated regressions of provincial energy consumption, we proceed to forecast the aggregate energy consumption in China. It is necessary to examine the capacity of forecasting accuracy for various specifications. This paper draws closely upon the strategies of Auffhammer and Carson (2008).

First, the information criteria of minimum AIC and BIC are referred to make a judgement for in-sample prediction ability. Second, in order to obtain an efficient out-of-sample forecast, the *pseudo* forecasting method is adopted for the best model selected by AIC and BIC. The main indicator is the root mean squared forecasting error (RMSFE) given as follows:

$$\mathrm{RMSFE} = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\frac{\sum_{t=t_1-1}^{T-1}(\ln(\mathrm{PEC})_{i,t+1} - \ln(\hat{\mathrm{PEC}})_{i,t+1|t})^2}{T - t_1 + 1}} \quad (2)$$

where n represents the total number of provinces. We first re-estimate different model specifications through t which is shorter than the full sample period, and then use the estimated coefficients to calculate the predicted per capita energy consumption for each province i in the next 1 year to obtain the forecast errors, $\ln(\mathrm{PEC})_{i,t+1} - \ln(\hat{\mathrm{PEC}})_{i,t+1|t}$. This procedure is repeated for the last 5 years in our sample to get a mean 1-step forecast error within a 5-year window for each province. They are then averaged for 28 provinces. The magnitude of RMSFE should be close to zero as forecasts improve.

The best model specification for forecasting the energy consumption is selected based on the above criteria comprehensively. Specifically, the standards of selection include a small 1-year RMSFE approaching to zero, a minimum AIC and a high R^2 near 1. The smallest 1-year RMSFE, among others, is particularly crucial in our selection.

3. Data

3.1. Energy consumption

China's energy consumption has been increasing dramatically since the reform of 1978. The annual growth rate increased from 2.5% in 1978 to the peak at 16.1% in 2004. The total energy consumption in 2008 was 3.3 billion tons of coal equivalents which is roughly 4 times that of the use in 1978.[7] We collect total energy consumption and population data (1996–2009) at

[7] The figures in this paragraph are author's calculations based on data from China Statistical Yearbook (1996–2009). OIA (2000) states that "coal equivalent" is a Chinese conversion factor for coal and other fuels are low-heat values. In China, average raw coal contains 20.93 GJ/metric ton (low heat), or 22.51 GJ/ton (high heat), assuming that low-heat values for coal are 93% of high-heat values. All the energy statistics are converted into "metric tons of standard coal

the province level from China Statistical Yearbook (1996–2009) and China Energy Statistical Yearbook (1996–2009) and compute per capita energy consumption (PEC) for 28 provinces.

3.2. Socioeconomic factors

Income is represented by per capita GDP (PGDP) in 1985 prices. As China does not report provincial deflators officially, we use the provincial CPI to convert nominal GDP into real values. The urbanization (URB), measured as the proportion of urban population, indicates demographic characteristics such as migration and population.[8] The change of economic structure is a typical phenomenon in transition economies. Since 1978, China has been becoming industrialized from a former agriculture-dominated economy due to improved economic structure. The industrial sector is widely believed as the main source of energy use and pollution producer (IEA, 2010). We take the economic structural changes into consideration and use provincial components of industry, agriculture, construction, transportation and telecommunication, and services to depict the changes of the economic structure. The proportion of each sector in the provincial economy is derived by the sectoral value-added output over GDP.

As an important part in transportation sectors, the automobile using is growing extremely fast with the increasing income. Accordingly, there is a growing demand for petrol. At the national level, per capita privately owned cars rose by 30.7% from 1990 to 2006. At the regional level, this number varies dramatically. In coastal provinces, private cars are no longer luxury goods and the demand is explosive in some big cities. By comparison, in the landlocked areas, especially rural areas, the demand of car is not as strong as those in rich regions since subsistence is still the theme of life. For example, per capita private cars in Guizhou province is only 8.7% of the figure in Beijing at the end of 2006. It is worth studying how this fact influences provincial energy needs. We use log per capita civil vehicles owned (CVO) to represent the impact of transportation development on energy use. All socioeconomic data (a balanced panel for 28 provinces from 1995 to 2008) are extracted from China Statistical Yearbook (1996–2009). The descriptive statistics of both energy-related and socioeconomic data are reported in Table 2.

4. Empirical results and discussion

4.1. Correlates of energy consumption at the disaggregate level

The estimates of different model specification are summarized in Table 3. Columns (1)–(4) adopt fixed-effects panel models without considering endogeneity and spatial dependence. The fixed-effects models with endogenous spatial lag dependence are reported in Columns (5)–(6).

The significantly positive estimates of log per capita real GDP in all columns indicate a positive relationship between income growth and energy consumption, even when we successively control for demographic changes, lagged energy consumption level, per capita privately owned cars and spatial interactions of energy use in Columns (2)–(5). Although the quadratic term of per capita GDP has significantly negative signs in all columns except for (6), one might not safely conclude the existence of an EKC between per capita GDP and energy consumption. One important reason

equivalent" (tce) in China, a unit that bears little relation to the heating value of coals actually in use in China. One tce equals 29.31 GJ (low heat) equivalent to 31.52 GJ/tce (high heat).

[8] Urbanization in our dataset is actually calculated from provincial permanent population excluding migration due to the lack of consistent data on inter-province migration.

Table 2
Descriptive statistics.

Variables	Obs.	Mean	Std. Dev.	Min	Max
ln(PEC)	392	0.473	0.559	−0.726	1.765
ln(PGDP)	392	7.859	0.678	6.371	9.638
Urbanization	390	0.363	0.179	0.146	0.891
ln(CVO)	392	−4.095	0.728	−5.490	−1.687
% industry	392	0.418	0.217	0.004	1.507
% agriculture	392	0.168	0.137	0.006	1.023
% Construction	392	0.074	0.058	0.006	0.423
% transport	392	0.073	0.049	0.001	0.666
% services	392	0.096	0.061	0.005	0.454

is that the quadratic term is presumed by *a priori*. We also experiment with higher-order polynomials and semi-parametric regressions to relax the posited model specification, while neither of them supports an EKC-relationship.[9] This suggests that, *ceteris parties*, the policies aimed at promoting economic growth tend to continuously push the primary energy demand, even when China becomes a high-income country.

In the time domain, the province level past and current energy consumption are positively correlated, as significantly positive coefficients of lagged energy consumption can be identified from Columns (3)–(4). The magnitude of this estimate is close to 1 (between 0.652 and 0.683), implying a relatively strong dependence of energy use for each province and a slow response to its former energy consumption. The more inactive responses, the slower are the provinces able to substitute inefficient capital with more efficient production materials. Hence, less energy can be saved. In this sense, this estimate also reflects some extent of the technological effects, as suggested by Auffhammer and Carson (2008).

There appears to be inter-dependence in local energy use. In Column (5), the spatial lag consumption is significantly positive, which indicates the copying behaviour in energy consumption among neighbouring provinces. The presence of spatial contagion of energy demand calls for the impending need of locally active participation in national energy conservation. The reduction in energy consumption in one province itself would "trigger off" the reduction in surrounding provinces due to the existence of copying behaviour, without jeopardising this province and its neighbours' economic growth. Consequently, these reductions at the disaggregate level would add up to the country's shrunk energy use and GHG emissions. In the opposite case, however, an increase in one area's energy need would result in even more demand at the aggregate level by enticing its neighbours to fuel more. Overall, local energy demand may exhibit either an amplifying or attenuating effect on country's aggregate energy consumption.

This finding is indicative for policy making of sustainable energy consumption and GHG reduction. The previous literature has highlighted sufficient financial transfers from developed countries (Tian & Whalley, 2010) and designing carbon tax on energy- and trade-intensive sectors (Liang, Fan, & Wei, 2007) in China, in order to help the country limit energy demand without dampening its productivity and international competitiveness. In the presence of the spatial effect, we further argue that China would be able to contribute more to the fight against the global warming

[9] The results of the robustness check are available upon request.

Table 3
Estimates of model specifications.

Indep. Vars.	FE-OLS				FE-SAR	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(PGDP)	1.248 (0.239)***	1.573 (0.235)***	0.714 (0.186)***	0.707 (0.175)***	1.542 (0.323)***	0.948 (0.317)***
ln(PGDP)^2	−0.034 (0.014)**	−0.058 (0.014)***	−0.032 (0.011)***	−0.032 (0.010)***	−0.442 (0.019)**	−0.009 (0.184)
URB		0.627 (0.133)***	0.172 (0.098)*			
ln(PEC$_{t-1}$)			0.683 (0.040)***	0.652 (0.040)***		
ln(CVO)				0.167 (0.040)***		
ln(time)					−0.516 (0.110)***	−0.505 (0.112)***
% industry						0.618 (0.207)***
% agriculture						−0.020 (0.193)
% transportation						−0.148 (0.134)
% construction						1.775 (0.516)***
% service						−2.272 (0.442)***
$\sum_{j=1}^{k} w_{ij}$ ln(PEC$_{j,t-1}$)					0.205 (0.087)**	0.120 (0.095)
Time fixed effects	Yes	Yes	Yes	Yes	No	No
Prov. fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	392	390	363	364	364	364
R^2	0.878	0.891	0.947	0.949	0.876	0.890
AIC	−571.268	−608.051	−829.565	−846.648	−551.214	−583.709
BIC	−507.728	−540.627	−763.360	−780.397	−535.625	−548.635
1-year RMSFE within a 5-year window	0.347	0.364	0.211	0.170	0.104	0.104

Note: a. The range of province specific lags. All estimates are significant at 1% except for Tianjin.
b. Sargan test suggests there is no overidentification. There is no AR(2) process in the error terms. Endogeneity test cannot reject the null hypothesis for the lag per capita energy consumption in Columns (3) and (4), but reject the null hypothesis for the spatial lag energy consumption in Columns (5) and (6) at the 1% significance level. The weak instrument robust inference is also rejected at the 1% significance level.

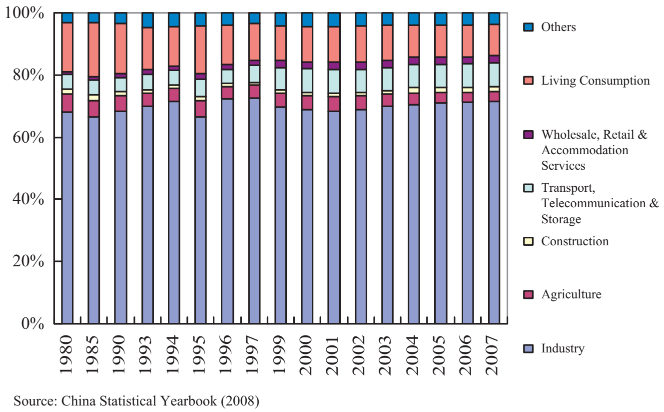

Fig. 2. Composition of energy consumption by sector, 1980–2007.
Source: China Statistical Yearbook (2008).

if it could aim energy conservation and limit energy consumption at a more disaggregate level within the country, especially in coastal and central provinces.[10]

Among various socioeconomic factors, urbanization substantially stimulates energy use (see Columns 2–3). An additional 1% increase in the proportion of urban population would raise the annual per capita energy needs by 1.87 ton of coal equivalent. A reason might be the increased urban population requires more industrial goods that are more energy-intensive compared to those needed for a rural life. Moreover, the government has long emphasized urbanization and the increased inter-province population flow from the 1990s has also speeded up the urbanization process. As a result, the demand-enhancing impact of urbanization on energy could be plausibly expected to continue. Along with the increased urban population and income, more ownership of cars also pushes energy demand (Column 4). An additional 10% increase in log per capita private cars tends to bring about more energy use by 1.67%.

As expected, the economic structure plays an unneglectable role in determining energy demand. Column (6) shows that the industrial expansion, especially the energy-inefficient plants, will dramatically raise the energy needs at an increasing speed. A 1% increase in the share of industrial value-added output in GDP would add 1.86 tons of coal equivalent to current per capita energy needs. Alarmingly, the most drastic increase of energy appears in construction sections: a 1% increase in its share in GDP would bring more 5.9 tons of coal equivalent to per capita energy consumption. In comparison, service sectors appear to be able to save energy. A 1% more value-added output in service sectors could reduce per capita energy needs by 9.7 tons of coal equivalent per annum. Although China is shifting toward more service sectors, total energy consumption has long been dominated by the needs from industrial sectors (Fig. 2). The average share of industrial energy demand in the last three decades was relatively stable, around 70%. Additionally, it is worth mentioning that the industrial share has consistently climbed from 68.5% in 2001 to 71.1% in 2006. As a result, the aggregate energy demand has also increased fast since then. As China is still in transition to an industrialized economy, particularly in the vast middle and western under

[10] We also re-estimate Column (5) for coastal, central and western regions individually and the spatial inter-dependence appears to exist in the former two regions with 1% and 10% significance levels respectively. In the western region, the spatial term also has positive estimate, but is statistically insignificant. The regional estimation results are upon request.

developed regions, it is hard to say that China will see a downward demand for energy in the near future. As suggested by much existing literature (*e.g.*, Soytas & Sari, 2006), it is of paramount importance to speed up the adjustment of the country's economic structure by developing "clean" service sectors. Nevertheless, this might seem less realistic and attractive for the western provinces since the income growth is still a dominating strategy for local governments as well as for poor people. An equivalent attention should also be given to construction sectors. Although its share in total energy use is low, the estimates clearly point to the largest positive marginal impact of total energy consumption. Overall, it could be inferred that under the current economic structure, China's increasing demand for energy will continue in at least the medium term.

Despite the government's continuous efforts to increase energy efficiency and curb GHG emissions, it is noteworthy that there is still much confusion as to the effects of technological advancement in China. The estimated year dummies are negative in Column (1) where we use these dummies to proxy for technological improvement that is common to all provinces in the same period. This underlines the energy-saving effects of technological development, especially from 1996 to 2001 when the magnitude of estimates decreased from −0.04 to −0.24. Nevertheless, this energy-saving influence became weaker between 2001 and 2005, as the magnitude of time fixed effects increased towards zero. Ma, Oxley, Gibson, and Kim (2008) find that it is the increased use of energy-intensive technology that drives up China's increasing energy intensity in that period. By contrast, in Columns (5)–(6) where time fixed effects are replaced by the logarithmic time trends in order to enhance the forecast capability by reducing estimated variables, the negative estimated coefficient implies that advanced technology is able to bring more efficient energy use over time and therefore, reduces the quantity of energy consumption.

These seemingly contradicting findings might be a result of what *a priori* assumption of the impact of technological progress on energy consumption one adopted.[11] As noted by Auffhammer and Carson (2008), a logarithmic time trend indicates decreasing marginal effects of technology improvement over time, considering the increasing marginal cost of using new technologies. Alternatively, the time fixed effects postulate constant technological influence. In addition, regional heterogeneity may matter. Some provinces may have more energy-related technical improvement due to considerable disparities across provinces in China in terms of levels of development, technologies, R&D investment and etc. As a result, these provinces experience a positive technological impact, while others may not.[12] Vollebergh, Melenberg, and Dijkgraaf (2007) demonstrate that spurious correlation which usually stems from estimating reduced-form panel models could be prevented by allowing for enough heterogeneity. Nevertheless, both the time fixed effects and log time trends accredit same technological influences to all provinces.[13]

[11] Besides, there are no conclusive results about technological effects in the existing literature. Most studies confirm the success of technological impact on increasing energy efficiency based on both macro evidence (Martinot and McDoom, 2000) and micro level evidence in Fisher-Vanden et al. (2004). Others hold the opposite opinions for various reasons, like the relatively long time needed to apply new technologies in infrastructures and transport (Grazi & Van den Bergh, 2008), the adverse effects of the efficiency-improving and quality-enhancing R&D investments (Fisher-Vanden and Wing, 2008), technical and economic barriers and local governments' attitude (Leung et al., 2004).

[12] When re-estimating models for coastal, central and western regions individually, we find that the logarithmic time trends are significantly negative in central provinces only, which may represent an energy-saving technological improvement, but the technological improvement in coastal and western provinces appears not to have benefitted energy saving.

[13] There is a need for further clarifying the heterogeneous technological impact on energy efficiency. One may allow for linear heterogeneous time trends in panels (Martinez-Zarzoso and Bengochea-Morancho, 2004; Vollebergh et al., 2007), or explicitly examine the technological influences in regressions (*e.g.*, the index of regional total factor energy efficiency in

Table 4
Scenarios for forecasts.

Scenarios	A		B		C	
	2009–2015	2016–2020	2009–2015	2016–2020	2009–2015	2016–2020
Mortality rate	2.04	1.83	2.04	1.83	2.04	1.83
Birth rate	1.37	1.30	1.37	1.30	1.37	1.30
Aggregate growth rate	0.58	0.48	0.58	0.48	0.58	0.48
Urban population growth rate	2.29	1.97	2.29	1.97	2.29	1.97
Real per capita GDP	7.20	4.50	8.03	8.03	9.03	9.03

Source: The first three population projections are from World Bank Population 2010–2050 Projects (http://go.worldbank.org/H4UN4D5KI0, accessed on 30 May 2011). The urban population growth rate comes from Population Division of the Department of Economic and Social Affairs of the UN (http://esa.un.org/wpp/Sorting-Tables/tab-sorting_population.htm, accessed on 30 May 2011). Real per capita GDP comes from EIU (2006) in Scenario A, the average World Bank (2011) forecasts in 2010–2012 based on author's calculations in Scenario B, the average IMF (2011) forecasts in 2010–2016 based on author's calculations in Scenario C.
Note: All figures are percentages.

4.2. Forecasting aggregate energy consumption

All model specifications give high goodness-of-fit, since all the R^2s are very close to 1. The 1-step RMSFE declines from Column (1) to (6) of Table 3, indicating higher power of out-of-sample forecasting. Clearly, the inclusion of spatial interactions across neighbour provinces gives the lowest RMSFE, as it decreases by 38.8% in Columns (5) and (6) compared with (4). The null hypothesis of equality of the provincial fixed effects is rejected by F-statistic at the 1% significance level in all specifications, which indicates significant regional heterogeneity in explaining energy consumption. Given this, the models at the provincial level should outperform these based on the national level in the existing literature in forecasting. Based on two information criteria and the 1-step RMSFE, the spatial model, *i.e.* Column (5), is considered as the most appropriate specification to forecast China's aggregate energy consumption from 2009 to 2020.[14] We also report the forecasts under the conventional dynamic panel with an EKC specification, *i.e.* Column (3), for the purpose of comparison.[15]

As summarized in Table 4, we first propose three scenarios combining the World Bank population projection with three levels of income growth at the national level. Then, the provincial population, urbanization and income growth rates are calculated according to their own contributions to the national increment of these socioeconomic indicators. The province's contribution of each socioeconomic is derived by its average share in the country during 1995–2008.

Fig. 3 depicts the forecasts of all scenarios. There would be a continuously increasing trend for China's total energy consumption from 2009 to 2020. Among various scenarios, higher income

Hu and Wang, 2006). However, as our focus is spatially interacted energy demand, further investigation of heterogeneous technological influence is beyond the scope of this paper.

[14] Although Column (6) has smaller BIC and AIC and higher R^2, it is not used for forecasting, considering China's on-going economic structure change and relatively long forecasting horizon (12 years). Since Columns (5) and (6) has same 1-year rolling RMSFE, it could be expected that they have equivalent power of forecasting.

[15] The out-of-sample forecasts of time fixed effects are obtained by using Auffhammer and Carson's (2008) method. Specifically, we regress the in-sample time fixed effects on an ordinal variable indicating years and detect the breaking point between 1997 and 2002 by repeating the same process of calculating 1-step RMSFE for the last 5 years as Section 2.2. The breaking point 1997 is selected based on the minimum 1-step RMSFE indicating the best quality of forecasting

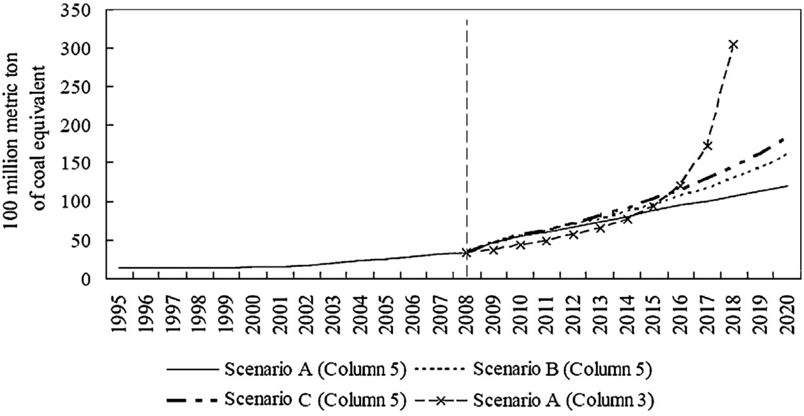

Fig. 3. Aggregate forecasts of China's energy consumption.

growth would generate more energy consumption in both model specifications (3) and (5), which is consistent with Auffhammer and Carson's (2008) finding in the case of CO_2 emissions. More specifically, the energy consumption rose from 3.3 billion metric tons of coal equivalent in 2008 to at most 18.2 billion in 2020. The observed average annual growth rate in the period of 1996 and 2008 was 7.4%. In all three scenarios using Column (5), the projected annual growth rates rise dramatically with an accelerated speed, from 5.8% in 2008 to 6.4%, 10.6% and 11.6% in scenarios A, B and C respectively. Comparing our forecasts with the results in the existing literature in Table 1, it is clear that controlling for the spatial effects dramatically brings up the aggregate forecasts for China's energy consumption, as demonstrated by Auffhammer and Carson (2008) in the case of forecasting China's CO_2 emissions.

Referring to Scenario A, we further compare forecasts based on Column (3) with Column (5) in Fig. 3. It can be seen that the forecasting line of Column (3) is below that of the Column (5) until 2015, but becomes increasingly high thereafter. An important implication is that using the standard dynamic panel model without considering the inter-provincial influence on energy use tends to under-forecast the short- or medium term energy demand (prior to 2015) but dramatically over-forecast the demand in the longer term.

As shown in Fig. 4, the elasticity of energy consumption would keep increasing till 2010 and then decline except in the case of using Column (3). The magnitude is greater than 0.5 in the decade starting from 2010. It may return to 0.48 in 2020 which is the same level as the elasticity in 2008. There appears to be rigidity in further reducing the elasticity of energy demand, supposing China maintains its significant economic growth.

In the meantime, our disaggregated model allows us to study separately which part of China appears as the driver of the country's soaring energy demand. The above forecasted pattern of energy demand is found to suggest significant geographic heterogeneity. As seen in Table 5, coastal provinces had the highest growth rate of energy use and are likely to continue to lead this growth within China in the near future, while less developed western provinces tend to experience the lowest growth rate. However, it is alarming that the elasticity of energy consumption with respect to GDP is higher than one in western and central provinces in the entire forecast horizon, which

accuracy. The predictions of time fixed-effects for the period during 2009 and 2020 are therefore calculated based on estimates of the aforementioned regression.

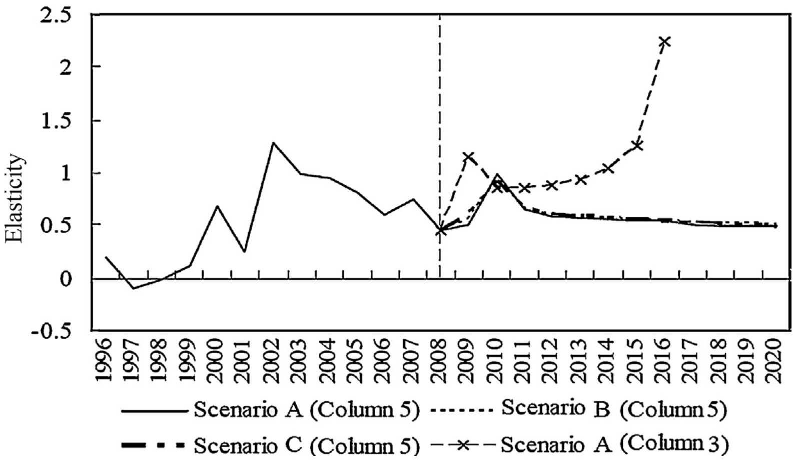

Fig. 4. Forecasts of elasticity of per capita energy consumption with respect to per capita real GDP.

Table 5
Diversified pattern of energy demand by region, scenario A and column 5.

	National	Coastal	Central	Western
Annual growth rate (%)				
1996–2008	7.38	8.18	6.85	7.52
2011–2015	10.01	12.45	8.14	4.67
2016–2020	6.45	7.76	5.15	2.79
Elasticity of GDP				
1996–2008	0.53	0.59	1.09	1.05
2011–2015	0.58	0.23	1.71	1.47
2016–2020	0.51	0.19	1.68	1.48
Intensity (annual reduction rate, %)				
1996–2008	0.528 (−4.23)	0.436 (−3.79)	0.616 (−4.40)	0.879 (−3.76)
2011–2015	0.454 (−6.13)	0.361 (−6.47)	0.608 (−3.39)	0.887 (−3.12)
2016–2020	0.335 (−5.59)	0.263 (−5.78)	0.516 (−3.13)	0.762 (−2.81)

indicates an accelerated growth in energy demand as income increases over time. The elasticity in the western region even appears not to decrease over 2016–2020. The western region also has the highest intensity in terms of tons of coal equivalent input per *yuan*. Although in general the intensity declines, most of this reduction is likely to happen in coastal provinces. Given these estimates, it could be plausibly expected that the coastal provinces are able to conserve more energy compared to western provinces. There would be a constraint of energy saving facing western provinces, if the efficiency of energy use could not be enhanced. As a result, in the long run, western provinces might take place of their coastal counterparts in driving the total energy demand in China.

5. Conclusion

This paper forecasts China's aggregate energy consumption in the next decade by estimating a spatial model at the provincial level. This allows us to take provincial heterogeneity and inter-dependence simultaneously into account and therefore, could substantially improve the accuracy of forecasts by nearly two fifth compared to that without controlling for spatial interactions. The analysis suggests that China may well continue to require a large amount of energy at least until 2020. In the period of the government's 12th "Five-year Plan" (2011–2015), the total energy demand would continue to grow by 45–61% if China could successfully maintain a moderate growth rate at 7–8% per annum, and the aggregate demand would be doubled by the end of 2020. Shifting the "growth engine" from the energy-intensive industrial sectors towards service sectors can significantly help China slow the increasing consumption of primary energy. The development and introduction of energy-saving technologies should arouse particular attention among policy makers, especially in western provinces, who experience the highest elasticity of energy with respect to income and the highest intensity of energy input in their economic growth. Moreover, strong and positive spatial effect implies that provinces, especially in coastal and central regions, are able to influence policies for economic growth and energy consumption of their neighbours by setting a good example and/or the diffusion of technological production processes. This spatial dependence also implies that controlling energy consumption at the disaggregated regional level would act as a "multiplier" by which one area's success could be spread to its neighbours and therefore bring about more induced effects at the aggregate level. This might significantly speed up the whole country's transition towards sustainable growth, if the Chinese government aims to achieve its goal in reducing CO_2 emissions and promoting sustainable energy use by 2020. In other words, China should pay more attention to acting locally, when aiming nationally or internationally. Moreover, this appears to be a win-win implementation strategy as it curbs the energy demand and CO_2 emissions without necessarily incurring economic burden.

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