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China's Farewell to Coal: A Forecast of Coal Consumption through 2020

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Abstract: In recent decades, China has encountered serious environmental problem, especially severe air pollution that has affected eastern and northern China frequently. Because most air pollutants in China are closely related to coal combustion, the restriction of coal consumption is critical to the improvement of the environment in China. In this study, a panel of 29 Chinese provinces from 1995 to 2012 is utilized to predict China's coal consumption through 2020. After controlling for the spatial correlation of coal consumption among neighboring provinces, an inverted U-shaped Environmental Kuznets Curve (EKC) between coal consumption per capita and GDP per capita in China is detected. Furthermore, based on the estimation results and reasonable predictions of key control variables, China's provincial and national coal consumption through 2020 is forecasted. Specifically, under the benchmark scenario, consumption is expected to continue growing at a decreasing rate until 2020, when China's coal consumption would be approximately 4.43 billion tons. However, if China can maintain relatively high growth rate (an annual growth rate of 7.8 percent), the turning point in total coal consumption would occur in 2019, with projected consumption peaking at 4.16 billion tons.

Key words: Coal consumption; Environmental Kuznets Curve; Spatial correlation; Panel data; Forecast

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1. Introduction

Alongside with rapid economic growth, China's coal consumption has soared over the past 30 years. Currently, the amount of coal consumed by China is larger than any other country in the world, and the annual growth rate of coal consumption was 7.8 percent between 2000 and 2012. As a result, coal has dominated China's energy mix – according to the data of the National Bureau of Statistics, since 1978, the share of coal consumption of total primary energy consumption has remained above 65 percent.

China's coal consumption has grown at nearly the same speed as its economic development, as coal has helped fuel China's rapid economic growth since the late 1970s. However, China's high dependence on and rapid growth in coal consumption have also brought about a series of problems.

The first problem created by China's extensive coal consumption is increasingly serious air pollution. A growing number of hazardous pollution incidents in recent years, represented by the fog and haze that have stricken most regions of eastern and northern China since early 2012, has not only posed a serious threat to citizens' health but also hampered China's sustainable growth. As Poon et al. (2006) have noted, the combustion of fossil fuels, especially coal, is one of the main causes of fine particles (PM2.5), which are the main components of this haze and fog pollution. Some recent studies have estimated the economic and welfare loss caused by the high concentrations of PM2.5 in China (Chen and He, 2014). In recent years, the increased air pollution has also attracted widespread international concern and hence damaged China’s international image.

The second significant problem related to coal consumption is the emissions of Greenhouse Gas (GHG) emissions generated by coal combustion. Since 1990, China’s CO_2 emissions have been growing at a remarkable speed. Currently, as the largest GHG emitter in the world, China accounted for approximately 25 percent of global CO_2 emissions. Given that climate change has become a global threat, Beijing has faced growing pressure from the international community to restrain CO_2 emissions.

The third problem, which is debatable but causing new concern, is that China is increasingly dependent on imported coal and energy supplies. Although China produces the most coal in the world, China has been a net importer of coal since 2007, and the imported amount has increased rapidly. In 2013, the net imported coal was approximately 320 million tons, and China’s ratio of dependence on coal imports reached a historical high of 8.1 percent. Because China had been a net importer of oil and gas since the 1990s, all main types of energy consumption rely on imports to varying degrees. Overall, the ratio of net imported energy to total energy consumption has risen rapidly from 3 percent in 1998 to 11 percent in 2011[1]. The expanding gap

[1] Data are available at: http://data.worldbank.org/indicator/EG.IMP.CONS.ZS (accessed on 27 April, 2015).

between energy production and consumption, especially in coal, threatens China's energy security and forms an important sustainable development bottleneck.

Fortunately, China has acknowledged these problems and has begun to make efforts to control coal consumption. The latest effort was made during the 2014 APEC summit, when China and the U.S. issued a *Joint Announcement on Climate Change*. According to the announcement, China vowed to achieve its peak CO_2 emissions and increase the share of non-fossil fuels in primary energy consumption to approximately 20 percent by 2030. As Auffhammer and Carson (2008) noted, in China, most CO_2 emissions come from coal consumption; therefore, whether China's CO_2 emissions can be reduced is highly dependent on the dynamics of coal consumption. Moreover, according to the historical experience of developed countries, such as the U.S., the UK and Germany, total coal consumption reaches its peak only after economic development has reached a certain level. Borrowing the notions of Grossman and Kruger (1991, 1995), an inverted U-shaped Environmental Kuznets Curve (EKC) described coal consumption. Therefore, the question of whether there is a peak in China's coal consumption is equivalent to asking whether there exists an EKC for coal consumption in China. So far, most studies on EKCs have focused on different types of environmental pollutants, and only a few have investigated EKCs for energy consumption (e.g., Suri and Chapman, 1998; Nguyen-Van, 2010). Thus far, no research has specifically examined the EKC for coal consumption. Additionally, many of the existing studies suffer from various problems. For example, spatial correlation in coal consumption is generally ignored, which implies biased estimates. By fully taking account of spatial correlation in coal consumption, this study utilizes the EKC framework and Chinese provincial panel data to estimate the factors that influence China's energy consumption and then forecasts China's total coal consumption through 2020 using reasonable predictions of the key determinants of coal consumption.

Since 1990, studies on the economic analysis of energy consumption have accumulated rapidly. In general, these studies can be classified into three categories:

The first strand of literature explores the causality of Chinese energy consumption and economic growth. Many researchers have examined the causality between energy consumption and income levels. For instance, Zhang (2000) found that the increase in income is the most important determinant of increasing energy consumption by decomposing aggregate CO_2 emissions into different factors. Lee and Chang (2008) and Chontanawat et al. (2008) verified Granger causality from energy consumption to income using a Vector Autoregression (VAR) and a Vector Error Correction Model (VECM), respectively. Using provincial panel data and VECMs, Chang (2010) found that a bi-directional Granger causality relationship between energy consumption and economic growth exists in China. In a recent study, Zhang et al. (2014) found evidence for the long-run causality from China's economic growth to energy consumption-related CO_2 emissions. In addition, Wang et al. (2013) tested and verified a similar relationship between economic growth and energy consumption using the concept of the ecological footprint.[2] Sheng et al. (2014) employed an instrumental regression technique to verify the positive relationship between economic growth and energy demand in China. However, this causal relationship between energy consumption and economic growth has not been found in all studies because many researchers have failed to find evidence of a causal relationship. In other words, the causal relationship is unstable, that is, subject to specific periods in the sample range (e.g., Zou and Chau, 2006; Soytas and Sari, 2006), to specific energy resources (e.g., Zou and Chau, 2006; Chang, 2010), or to certain industries (e.g., He et al., 2008). For instance, Soytas and Sari (2006) found that causality existed only over the short run and may weaken over time. Moreover, He et al. (2008) found that the causality relationship between energy consumption and economic growth is significant only in secondary industries.

The second body of literature examines the existence of EKC for energy consumption. The empirical existence of an EKC was first proposed by Grossman and Kruger (1991, 1995), arguing that there is an inverted U-shaped relationship between environmental quality and economic growth: during the early stages of economic growth, pollution aggregates and the environment deteriorates; after the peak level of pollution is reached, pollution decreases and the environment improves as the economy continues

[2] The ecological footprint is a measure of human demand on the Earth's ecosystems. It is a standardized measure of demand for natural capital that can be compared with the planet's ecological capacity to regenerate. As a result, the ecological footprint can be used to estimate how much of the Earth (or how many planet Earths) is (are) needed to support humanity if a given lifestyle is followed by every human being on the Earth.

to grow. The vast majority of the research on EKC has investigated various pollutants, including atmospheric pollutants (such as SO_2, CO_2, biological oxygen demand, nitrogen oxides and smoke), water pollutants (such as chemical oxygen demand, COD), deforestation, and solid waste. Because many literature reviews are available for this particular strand, we omit such a description. The second strand is focused on the EKC of energy consumption. Overall, some recent studies use energy consumption as a proxy for environmental pressure and estimate the EKC relationship between energy consumption and economic development because the estimation results for EKC studies are not consistent (Stern, 2004; Dinda, 2004; Auci and Becchetti, 2006). For example, Suri and Chapman (1998) verified the existence of an energy consumption EKC and found that exports and imports of industrial goods drive the upward and downward slopes, respectively. Yoo and Lee (2010) detected a statistically significant inverted U-shaped relationship between per capita consumption of electricity and per capita income. However, as stressed in the survey by Dasgupta et al. (2002), numerous critics have challenged the conventional EKC. The differences in empirical results among EKC examinations are so large that there is not yet consensus regarding whether the EKC relationship is valid. For example, Cole et al. (1997) found the substantial existence of an energy consumption EKC only when atmospheric pollutant indicators increase monotonously with income, otherwise the energy consumption EKC is not observed. Luzzati and Orsini (2009) examined energy consumption using panel data for the absolute value of energy consumption. They conduct an analysis using parametric and semi-parametric regressions simultaneously for the world as well as for a single country. However, the energy consumption EKC is observed neither for the world nor for the single country. Saboori and Sulaiman (2013) analyzed the EKC using Autoregressive Distributed Lag (ARDL) and co-integration bounds testing methods and did not find support for an inverted U-shaped relationship (EKC) when aggregated energy consumption data were used. Moreover, there are two main deficiencies in the second group of studies. The first is that energy consumption is usually chosen as the proxy indicator for environmental pressure, and in general, the magnitudes used are calculated by aggregating weighted energy resources combustion. However, compared to data of electricity or coal consumption, the errors may accumulate. Thus, the accuracy of such data is low and less reliable. This is likely to yield biased estimations. The second shortcoming is that, except for electricity, investigations focusing on specific energy resources are still lacking. For example, the existence of an EKC for China's coal consumption remains uncertain. Such research could explicitly examine the inverted U-shaped coal-income relationship, which has been seldom noted by economists. However, conducting this research is of overriding importance because CO_2 emissions are positively related to coal consumption (Suri and Chapman, 1998). Hence, the downward slope of the CO_2 EKC after the turning point is largely determined by the peak and downward slope of the coal EKC, other conditions being equal. Furthermore, based on the examined EKC relationship between energy consumption and economic development, energy demand can be forecasted. For example, You (2013) first employed different specifications that incorporated the spatial correlation of energy consumption to estimate the inverted U-shaped relationship between carbon emissions and GDP per capita in China and then projected CO_2 emissions using provincial data from 1995 to 2007.

The third branch of literature accounts for the spatial correlation of energy consumption among neighboring regions. According to the First Law of Geography (Tobler, 1970), spatial correlation implies that all geographical objects and attributes depend on each other due to spatial distribution, and there is clustering, randomness and regularity in the distribution. In other words, the determiners of certain regional environmental conditions are not limited to the geographic area in the hypothesis. Because, as Anselin (1988, 2001) stressed, there is explicit spatial correlation in pollutant emissions or energy consumption, correction for spatial correlation could greatly improve forecasts. Therefore, omitting the spatial effects may yield biased predictions. Rupasingha et al. (2004) and Maddison (2006) used Spatial Error Modeling (SEM) and Spatial Lag Modeling (SLM) to control for spatial correlation and analyze the pollutant EKC in the U.S. using county-level and country-level data, respectively. They both find that spatial effects are important in understanding toxic pollution in the U.S. counties. Similarly, Poon et al. (2006) employed LM robustness checks for spatial effects. Other research that has verified the existence of spatial issues in environmental pollutant emissions includes Giacomini and Granger (2004), David Maddison (2006), and Auffhammer and Steinhauser (2007). As for China, an increasing number of studies on environmental problems consider spatial correlation.

For instance, Guo and Zheng (2012) empirically analyzed a wide range of industrial pollutant EKCs based on different spatial fixed effects models and concluded that there was strong spatial component within Chinese environmental quality. Cattaneo et al. (2011) utilized spatial ADL models to verify the spatial dependence of coal consumption among Chinese provinces and forecasted China's coal consumption until 2010.[3] Other studies supporting spatial relevance in China include Ying (2003), Aroca et al. (2006), and Girardin and Kholodilin (2009). Therefore, China's coal consumption may also have spatial relevance as with the consumption of other energy resources and of pollutant emissions.

As a result, the contribution of this paper is threefold. First, the spatial correlation in coal consumption among adjacent provinces is taken into full consideration. Estimation bias can be amended by controlling for spatial effects, and the forecasts based on these estimation results should therefore be more accurate. Second, to the best of our knowledge, this paper makes the first effort to examine the existence of an EKC for coal consumption using provincial panel data for China. The implication of this examination is straightforward: if there is indeed an inverted U-shaped EKC for China's coal consumption, there is possibility for China to reach the turning point in coal consumption on condition that China maintains sustainable and rapid economic

[3] However, there are several defects in Cattaneo et al.'s (2011) study. The most important problem is that endogeneity due to bilateral causality between coal consumption and GDP per capita is simply ignored. Another obvious problem is that the accuracy of the model used for prediction was not evaluated; therefore, the forecast results are actually far from the actual data. For instance, according to the China Statistical Yearbook 2014, China's industrial coal consumption was 2154 million tons in 2005 and 2960 million tons in 2010. However, Cattaneo et al. (2011) forecasted that national industrial coal consumption would be less than 1400 million tons in 2005 and no more than 1690 million tons in 2010. Considering the fact that they utilized provincial data until 2002, the forecast errors are sizeable.

development.[4] Third, using rigorous estimation results controlling for spatial correlation, we make predictions for national and provincial coal consumption using provincial information from 2013 to 2020. Compared with forecasts produced by pure scenario analysis, our forecasts have solid foundations and are therefore more accurate and reasonable. These predictions could also be used as important references for policy makers to control China's coal consumption before 2020, especially for formulating the reasonable total coal consumption target in the 13th Five-year Plan (2016-2020).

The remainder of this paper is organized as follows. In section 2, the data used in the study are first interpreted, and the set-up of the empirical model and the forecasting methods are explained. In section 3, the regression results are reported, and the forecasts based on the estimation results are conducted. In section 4, some important findings of the regression results and the dynamic features of predicted national and provincial coal consumptions are discussed. Finally, section 5 concludes and identifies some relevant policy implications.

2. Methods

2.1 Data

[4] As an anonymous reviewer stressed, the improvement of environmental quality may not be a natural process even if the inverted-U shaped EKC is proven to exist, because the shape, size and position of the EKC might probably be affected by corresponding policies. Some recent studies have investigated the influences of policy on EKC in China. For instance, He and Wang (2012) have verified that China's development policy has significantly affected the "height" and "slope" of EKC in China. Similarly, Hao and Liu (2015) also verified that the foreign economic and trade policies of China have had considerable impacts on China's EKC for CO_2 and SO_2.

In recent years, China's economic growth has been fueled by rapid increases in coal consumption. According to the China Energy Statistical Yearbook, coal consumption has accelerated since the mid-1990s, and the average annual growth rate of coal consumption in China was as high as 10 percent (*China Energy Statistical Yearbook*, 2002-2006) during the 10th Five-year Plan (2001-2005). Currently, China's coal consumption accounts for approximately 50% of world level. Because there were no statistics for provincial coal consumption before 1995, the data series dates to 1995[5].

In addition to coal consumption, economic and social indicators are also utilized as main explanatory variables. The following indicators are used:

(1) **GDP per capita (at 1978 constant prices)**. There are many studies suggesting the relevance of energy consumption to per capita income and the existence of an EKC for coal consumption (e.g., Suri and Chapman, 1998; Bloch et al., 2012). Thus, GDP

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5 As an anonymous reviewer pointed out, there is a caveat in using the statistics of coal consumption from the China Energy Statistical Yearbook. It is noteworthy that, during the study period, the National Bureau of Statistics (NBS) has revised the number of China's energy consumption at least twice. In the latest revision in 2015, China's coal consumption data in 2013 was upward adjusted from 3.62 to 4.05 billion tons. Some researchers have also questioned the accuracy of China's energy statistics (e.g., Sinton, 2001; Guan et al., 2012). Despite the potential data flaws, the empirical estimations of this study are still meaningful, of which the reason is twofold. Firstly, the data of coal consumption released by NBS are used as the benchmark, and the provincial coal consumptions are calibrated based on the ratio to the provincial total. As stressed by Guan et al. (2012), China's provincial energy statistics seem to be more skeptical than the NBS' statistics due to opaque reporting and validation as well as politically intentional manipulations. Comparably, NBS' data are more reliable (e.g., Wu, 2006; Chow, 2006). Secondly, when the historical energy statistics are revised, the energy consumptions of all years are scaled up by a similar percentage. As a result, the forecasts of China's projected coal consumptions of this study could at least reveal the future trend of coal consumption. In other words, the important qualitative conclusions, including whether the turning point of coal consumption would be reached or whether the coal consumption would continue to rise in the near future, would not change due to data adjustment. After all, by June 2015 when this study was finished, the details of the latest revision of energy statistics by NBS have not been released, and the adjusted provincial coal consumptions before 2013 are yet unknown. As a result, the statistics from China Energy Statistical Yearbook are the best data that could be used at the moment.

per capita and its square term are introduced at the same time to test for a possible EKC relationship. To maintain comparability, the data for GDP per capita have been converted to constant 1978 prices.

(2) **Ratio of the secondary industry value added to GDP.** Many researchers have noted that the secondary industries are the main coal consumers (IEA, 2010). This is especially true for China. Because the importance of secondary industry has increased dramatically since the reform and opening of China, the average ratio was above 40 percent from 2000 to 2012 (China Statistical Yearbook 2014). Thus, this ratio is included in this study as an independent variable.

(3) **Urbanization rate.** In general, compared to those in rural regions, citizens in urban areas tend to consume more industrial goods, and many Chinese cities still rely on coal for heating. As a result, China's rapid urbanization may also trigger coal consumption. This study utilizes the urbanization rate to control for the demographic characteristics that are associated with urbanization and may thus affect coal demand.

(4) **Trade openness.** Trade has also played an important role in China's economic growth. In the decade following China's accession to the World Trade Organization in 2000, the average growth rate of China's foreign trade (the sum of import and export volumes) was as high as 17.78 percent (various years of the China Energy Statistical Yearbook). Trade openness, measured by the ratio of total import and export volumes

to GDP, is a commonly used variable in EKC-related studies (Cole et al., 2003; Ang, 2009). Additionally, in a recent study, Shahbaz et al. (2013) utilized Autoregressive Distributed Lag (ARDL) and Vector Error Correction Model (VECM) methods to verify that foreign trade is closely related to China's energy consumption and economic growth. Following this research, this study uses trade openness as a control variable.

We utilize provincial data in the estimations and forecasts.[6] The provincial total coal consumption data from 1995 to 2012 are extracted from the China Energy Statistical Yearbooks 1996-2013. Provincial population data are collected from the China Statistical Yearbooks 1996-2013. Other socioeconomic indicators (including GDP per capita, ratio of secondary industry value-added to GDP, the total amount of imports and exports) of all provinces are obtained from various years of provincial Statistical Yearbooks and China Compendium of Statistics 1949-2008. As a summary, the descriptive statistics of all variables used in this study are in Table 1.

Table 1 Descriptive Statistics.

Variable names	Obs.	Mean	Std. Dev.	Min	Max	Unit	Meaning
CoCoperc	522	220.25	190.06	18.57	1470.77	Kg per year	Coal consumption per capita
GDPperc	522	4654.72	4356.37	575.81	30104.70	Yuan (1978 constant prices)	GDP per capita
URB	522	42.64	16.77	13.52	89.30	%	Urbanization rate
Second ratio	522	45.13	7.85	19.74	59.05	%	The secondary industry rate

[6] Currently, there are 22 provinces, 4 Centrally Administered Municipalities, and 5 autonomous regions in the mainland of China. Because these entities are administratively equal, we use the term "province" throughout the paper. As Chongqing became a new municipality only in 1997, we combined Chongqing and Sichuan to maintain comparability of the data. Tibet is excluded due to a lack of data. Therefore, there are 29 provinces in our database.

Trade openness	522	0.32	0.40	0.03	2.05	Trade openness

2.2 Regression Specifications

As mentioned previously, the EKC relationship between coal consumption and economic growth in China is examined. Following Auffhammer and Carson (2008) and You (2013), the benchmark estimation equation is as follows:

$$\begin{aligned}\ln(CoCoperc_{it}) = \beta_0 + \beta_1 \ln(\mathrm{GDP}perc_{it}) + \beta_2 \ln^2(\mathrm{GDP}perc_{it}) + \beta_3 \ln(CoCoperc_{i,t-1}) \\ + \beta_4 \sum_{j=1}^{k} w_{ij} \ln(CoCoperc_{j,t-1}) + \beta_5 \overline{X_{it}} + \alpha_i + \eta_t + u_{it}\end{aligned} \tag{1}$$

where $\beta_0 \sim \beta_5$ are the estimated coefficients; $\ln(CoCoperc_{it})$ represents coal consumption per capita of province *i* at time *t*, and $\ln(\mathrm{GDP}perc_{it})$ represents real GDP per capita in logarithmic form. w_{ij} indicates the weights of spatial dependence across provinces; $\sum_{j=1}^{k} w_{ij} \ln(CoCoperc_{j,t-1})$ represents the provincial spatial effects of coal consumption of all neighboring provinces of province *i*, where *k* denotes the number of province i's neighbors. $\overline{X_{it}}$ is a vector consisting of other control variables, including the ratio of secondary industry value-added to GDP, urbanization rate and trade openness. These control variables are frequently used in existing literature on the relationship between energy consumption or its related environmental quality and economic development in China, including Auffhammer and Carson (2008), Hao et al. (2014), and Zhang et al. (2014). α_i and η_t are individual fixed effects and time fixed effects, respectively. u_{it} is an unobservable and uncontrolled random disturbance item. $\ln(CoCoperc_{i,t-1})$ and $\sum_{j=1}^{k} w_{ij} \ln(CoCoperc_{j,t-1})$ represent the first-order lag of provincial coal consumption and the influence of neighboring provinces' coal consumption for the previous period, respectively. The meanings of these two items will be elaborated in the ensuing paragraphs.

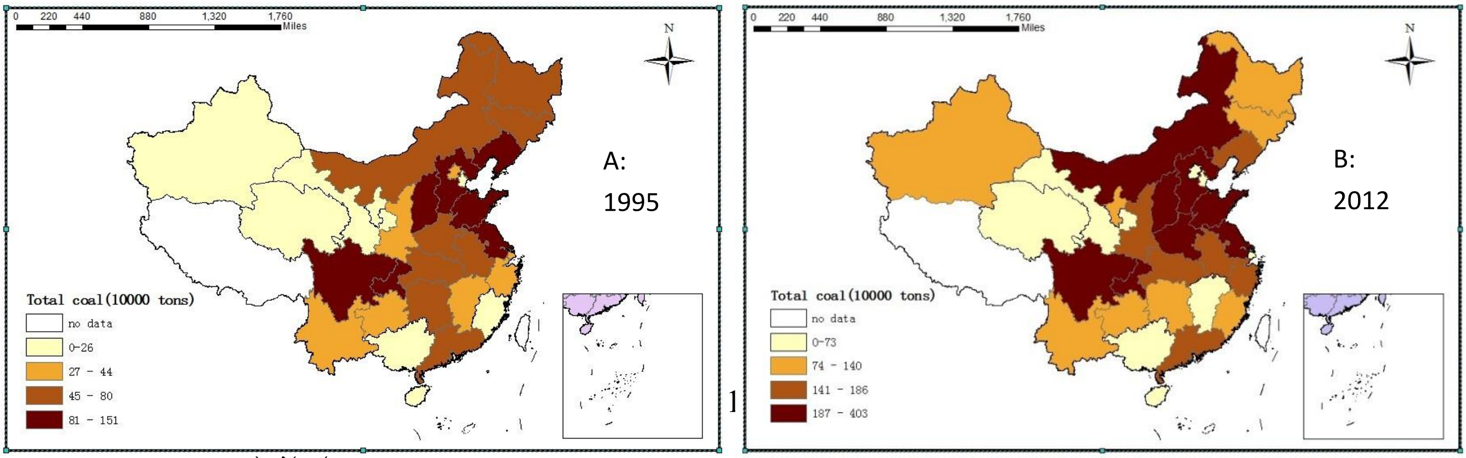
$\ln(CoCoperc_{i,t-1})$ is the lagged per capita coal consumption in logarithmic form. The introduction of the lagged term captures the influence of the coal consumption of the previous period on the coal consumption of the current period because the momentum of coal consumption may persist over time; therefore, current coal consumption might be affected by historical consumption.[7] It is noteworthy that Eq. (1) is a dynamic equation because lagged coal consumption is introduced as an explanatory variable.

Finally, $\sum_{j=1}^{k} w_{ij} \ln(CoCoperc_{j,t-1})$ captures the possible influences of neighboring provinces' coal consumption on province i in the current period. These influences occur through spatial correlation in coal consumption. It should be noted that, following You (2013), we assume the spatial effects occur in the following period. The logic behind this assumption is straightforward: it takes time for a province to learn the economic development and energy usage styles of its neighbors.[8]

[7] One possible explanation for the momentum of coal consumption is that some socioeconomic factors that affect coal consumption may not change dramatically over time. For instance, the machinery, equipment and facilities that are related to coal consumption (such as boilers and blast furnaces in the steel plants) generally have a lifespan, and residents' coal consumption habits only change gradually.

[8] It is also necessary to note that we focus on coal consumption instead of pollutant concentrations or emissions. Because air and water pollutants (such as SO_2, CO_2 and COD) have relatively high mobility, the spatial correlations of air and water pollutants may be exhibited more quickly than those of energy usage.

To illustrate the spatial correlation of coal consumption more intuitively, we map the coal consumption of all 29 provinces under investigation in 1995 and 2012 in Panels A and B, respectively, of Figure 1. There are two main observations from the Figure 1. First, in both years, there are clear signs of spatial correlation in coal consumption. For instance, in both years, the 6 provinces in northern China (Shanxi, Inner Mongolia, Hebei, Liaoning, Shandong and Jiangsu) belong to the group whose coal consumption per capita is relatively high (the top and second-highest categories). Conversely, the 4 provinces in the southwest China (Yunnan, Guizhou, Guangxi and Hainan) have relatively low per capita coal consumption in both years. The second observation from Figure 1 is that the basic pattern of coal consumption remained constant during the sample period of nearly two decades. Considering rapid economic and social development, the persistent pattern of coal consumption also, to some extent, indicates the role of momentum in coal consumption. There are two possible explanations for the clear pattern of China's coal consumption. First, according to Poon et al. (2006), the major coal-consuming industries are the electricity generation, iron and steel, construction materials and chemical industries. Among these industries, electricity generation has particularly increased coal demand. Furthermore, Shandong, Guangdong and Jiangsu, had the most thermal power plants in the country by 2012. Thermal power greater than 100 billion Kwh is generated in these three leading provinces (*China Energy Statistic Yearbook*, 2013). Second, despite the electricity industry, other coal-intensive industries, such as iron and steel, construction and chemicals, are concentrated in the same 6 regions. This is the case in Sichuan, Hebei, Shanxi, Shandong, Inner Mongolia and Jiangsu. The existence of concentration in coal consumption suggests simulation of productive coal consumption behavior of adjacent provinces, and there may be spatial inter-correlation in coal consumption.



For this paper, similar to the approaches of Auffhammer and Carson (2008) and You (2013), the spatial inter-correlation of provincial coal consumption is calculated by $\sum_{j=1}^{k} w_{ij} \ln(CoCoperc_{j,t-1})$. As LeSage and Pace (2010) and Plümper and Neumayer (2010) noted, the key variable needed to calculate this expression precisely is the spatial weight matrix w_{ij}. There are several ways to construct w_{ij}, and the most commonly used criteria for judging whether two areas are adjacent are the distance between two areas and geographic contiguity. Following the classical literature on spatial econometrics, such as Abreu et al. (2005) and Madariaga and Poncet (2007), we choose a threshold distance of 1624 km. In other words, if the linear distance between two capital cities is less than 1624 km, the two provinces are considered spatially adjacent, corresponding to w_{ij}=1 and suggesting that spatial correlation in the coal consumption of these two provinces exists. If the linear distance between the two capital cities is greater than this threshold level, then w_{ij}=0, implying that there is no significant spatial relationship between these two provinces.[9,10] Then, the matrix is row standardized to eliminate the scale effects. After row standardization, the sum of elements in each row is one, and the elements denote the spatial correlations of corresponding provinces. This procedure meets all the requirements stressed by Giacomini and Granger (2004) for a suitable spatial weight matrix. Then, we multiply the matrix by the coal consumption of the neighbors of province *i* in the previous period to calculate $\sum_{j=1}^{k} w_{ij} \ln(CoCoperc_{j,t-1})$. The values of this term are utilized as the observations for the spatial influence of other provinces on province *i*.

2.3 Estimation Methods

To determine the best model for forecasting, three different methods are utilized to estimate Eq. (1), including the Fixed Effects (FE) estimator, Biased-Corrected Least Square Dummy Variable (LSDVC) model and Generalized Method of Moments (GMM). Because there must be some province-specific factors that may affect coal

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[9] Some other studies of China used similar threshold distances. For instance, Ying (2003) utilized 2000 km as the threshold distance because he believed that the cities within 2000 km in China are spatially dependent. In a recent study, You (2013) used 1000 miles (1609 km) as the threshold distance.

[10] Besides this criterion, other studies have used the reciprocal of the geographic distance between two cities i and j as the corresponding element w_{ij} in the weight matrix (e.g. Plümper and Neumayer, 2010; Klemm and Van Parys, 2012). Others have set w_{ij} to 1 only if the two regions share a border (e.g., Poon et al., 2006; Hao et al., 2014). In fact, the choice of spatial weight matrix is key for spatial econometric analysis (Lesage and Pace, 2010), and Plümper and Neumayer (2010) have tested several different types of spatial weight matrixes to show the importance of choosing the correct type of spatial weight matrix.

consumption but are invariable over time, there should be heterogeneity across provinces. Therefore, the FE estimator should be utilized to control for this heterogeneity, and the estimation results of FE can be treated as a benchmark for other, more advanced and complicated estimation methods, following Auffhammer and Carson (2008) and You (2013). Because the FE estimator still has some defects and limitations, two additional estimation methods, LSDVC and GMM, are employed. The reasons for choosing these two complementary estimation methods are explained below.

First, although FE estimator can address heterogeneity, it cannot address the endogeneity problem that may stem from a bilateral causal relationship between the dependent and independent variables or neglected variables. This is also the most important problem in Cattaneo et al. (2011) in an earlier effort to forecast China's industrial coal consumption using disaggregated provincial information. According to Eq. (1), per capita coal consumption is the dependent variable, and the GDP per capita is an explanatory variable. However, as Fei et al. (2011) and Zhang and Xu (2012) noted, there is bilateral causal relationship between energy consumption and GDP per capita, and because there must be some factors that may influence coal consumption but are not able to be introduced into the specification, an endogeneity problem may exist. To address endogeneity, the system GMM developed by Arellano and Bond (1991) is utilized. Moreover, Conley (1999) has proved that the estimated coefficients produced by system GMM are consistent, even when there is spatial correlation.

Furthermore, Nickell (1981), Kiviet (1995), and Judson and Owen (1999) utilized Monte Carlo Simulation to prove that LSDVC outperforms GMM in bias or Mean Squared Error (MSE) under certain circumstances. Hence, the LSDVC model is also compared with the GMM model.

2.4 Forecasting Technique

This paper forecasts provincial coal consumption from 2013 to 2020 based on the model with the highest predictive power. To evaluate the predictive power of each model, in-sample forecasts of coal consumption during the last five years (2008-2012) are conducted, and then, the in-sample forecast results are compared with the actual data. Specifically, we utilize Root Mean Squared Forecasting Error (RMSFE) and Average Mean Squared Forecasting Error (AMSFE) to determine forecast accuracy. The formulas for RMSFE and AMSFE are as follows.

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

$$AMSFE = \frac{1}{\mathrm{n}} \sum_{i=1}^{n} \frac{\sum_{t=t_1-1}^{T-1} \left|(\ln(CoCoperc)_{i,t+1} - \ln(Co\hat{C}operc)_{i,t+1|t})\right|}{T - t_1 + 1} \quad , \quad (3)$$

where n represents the number of provinces and T the number of years in the sample range; t_1 is the end of the estimation period (t_1=2007 in this paper). We first calculate the values of RMSFE and AMSFE for each province, and then obtain average RMSFE and AMSFE for all 29 provinces. The lower the average RMSFE and AMSFE, the more accurate the forecast. Therefore, the strategy is simple and clear: let the data speak for themselves. Without stating hypotheses on the results of the different estimation methods, we simply consider the in-sample forecasts of each model and then compare their average RMSFE and AMSFE values. The model with the lowest RMSFE and/or AMSFE is chosen as the benchmark model. For the out-of-sample forecast, we first predict the values of the key variables that influence China's coal consumption (i.e., the explanatory variables of the benchmark model), and then, the predicted provincial coal consumption and key explanatory variables are substituted into the benchmark model to forecast provincial coal consumption for each year. The sum of predicted provincial coal consumption provides the projected national coal consumption. It is noteworthy that we utilize provincial information to forecast national coal consumption. As stressed by Auffhammer and Steinhauser (2007) and Cattaneo et al. (2011), more accurate predictions may be generated using disaggregated data (e.g., province-level data) compared with aggregated national data because disaggregated data may account for regional heterogeneity (Baltagi et al., 2012), which is a significant problem in the Chinese context. Therefore, using provincial data rather than national data greatly improves forecast performance (Marland, 2003; ERI, 2004; Jiang and Hu, 2006).

In conclusion, to obtain the best model for the forecast, we employed FE, GMM and LSDVC to estimate Eq. (1) and compared their results and the accuracy of their in-sample forecasts by calculating the RMSFE and AMSFE values.

3. Results

3.1 Estimation Results for Eq. (1)

As mentioned in the previous section, the FE, GMM and LSDVC methods are utilized to estimate Eq. (1). The estimation results are presented in Table 2.

Table 2 The estimation results of Eq. (1).

Indep. Vars.	FE-OLS		GMM			LSDVC		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(\mathrm{GDP}perc_{it})$	1.419^{***}	1.009^{***}	1.482^{***}	1.053^{***}	0.595^{***}	0.848^{***}	0.733^{***}	1.192^{***}
	(0.186)	(0.199)	(0.144)	(0.114)	(0.211)	(0.223)	(0.222)	(1.192)
$\ln^2(\mathrm{GDP}perc_{it})$	-0.0680^{***}	-0.0445^{***}	-0.0878^{***}	-0.0606^{***}	-0.0379^{***}	-0.0427^{***}	-0.0420^{***}	-0.0570^{***}
	(0.011)	(0.012)	(0.009)	(0.007)	(0.014)	(0.014)	(0.014)	(-0.057)
$\ln(CoCoperc_{i,t-1})$	0.618^{***}	0.566^{***}	0.901^{***}	0.792^{***}	0.804^{***}	0.688^{***}	0.683^{***}	0.697^{***}
	(0.029)	(0.030)	(0.031)	(0.017)	(0.048)	(0.033)	(0.031)	(0.034)
$\sum_{j=1}^{k} w_{ij} \ln(CoCoperc_{j,t-1})$			0.119^{***}	0.125^{***}	0.156^{***}	0.120^{**}	0.126^{**}	0.245^{***}
			(0.035)	(0.0246)	(0.046)	(0.051)	(0.051)	(0.245)
Second ratio		1.071^{***}		0.842^{***}	0.825^{***}	0.890^{***}	0.993^{***}	
		(0.213)		(0.240)	(0.230)	(0.284)	(0.280)	
URB					0.408^{***}		0.676^{***}	0.842^{***}
					(0.001)		(0.001)	(0.008)
Trade openness					-0.110^{***}			-0.148^{*}
					(0.037)			(-0.148)
ln(time)								-55.69^{**}
								(-55.689)
Constant	-5.013^{***}	-3.466^{***}	-6.257^{***}	-4.442^{***}	-2.587^{***}	-3.44291	-2.884952	417.4961
	(0.743)	(0.787)	(0.586)	(0.451)	(0.877)	(0.208)	(0.213)	(0.265)
Turning point	33990.06	83874.65	4626.87	5932.01	2564.72	20532.05	6162.21	34757.14
RMSFE/AMSFE	0.43/0.42	0.41/0.39	0.25/0.22	0.27/0.25	0.27/0.25	0.36/0.35	0.34/0.33	0.52/0.50
Obs./IV	493	493	493/62	493/129	493/190	493	493	493
Arellano Bond AR(1) test	-	-	-2.78	-2.66	-2.57	-	-	-
			(0.005)	(0.008)	(0.010)			

Arellano Bond AR(2)test	-	-	-0.62	-0.41	-0.65	-	-	-
			(0.535)	(0.683)	(0.514)			
Hansen test	-	-	26.70	28.72	26.16	-	-	-
			(1.000)	(1.000)	(1.000)			

Note: [a] Standard Errors (SE) are given in the parentheses below the corresponding coefficients of the independent variables. [b] P-values for all tests are reported in the parentheses below the statistics. [c] *, **, and *** indicate significant at 10%, 5%, and 1% level, respectively. The logarithmic lagged coal consumption, $\ln(CoCoperc_{i,t-1})$, GDP per capita and secondary industry ratio are used as instrumental variables.

In Table 2, models (1) and (2) are estimated using a panel data FE method. Models (3)-(5) are estimated by system GMM; models (6)-(8), by LSDVC. It is noteworthy that in models (3)-(8), spatial correlation is controlled for by incorporating the term $\sum_{j=1}^{k} w_{ij} \ln(CoCoperc_{j,t-1})$. For each model, we report the specifications with all coefficients that are statistically significant at least at the 10% level.

Because system GMM and LSDVC estimations have controlled for potential endogeneity, and because spatial integration is introduced in GMM and LSDVC estimations, they generate more reliable and reasonable results than the FE estimator. Therefore, the benchmark model for the forecast is chosen from between the GMM and LSDVC models. Because model (3) has the lowest RMSFE and AMSFE values, it has highest in-sample forecast accuracy; therefore, we utilize model (3) for the out-of-sample forecast.[11]

3.2 Forecasting China's Coal Demand for the 2013-2020 period

As mentioned previously, the out-of-sample forecast is based on the in-sample forecast results. Because model (3) in Table 2 has the lowest RMSFE and AMSFE values, it is utilized as the benchmark forecast model. Specifically, the forecast procedure is interpreted as follows.

Before the coal demand forecast is conducted, it is vital to forecast the explanatory variables used in model 3. Because an EKC relationship between coal consumption and GDP per capita

[11] Actually, this paper considered specification (5) and (7) in Table 2 for the corresponding forecasts. The forecast results are similar to those of this study. Due length concerns, the predictions using alternative specifications are not reported in this paper but are available upon request.

exists and the coefficient of GDP per capita is quite large in magnitude, GDP per capita is the most important indicator of forecast coal consumption. Many academic institutes and researchers have issued various short- and medium-term predictions of China's GDP growth rate. To ensure the authority and objectivity of the forecast results, the projected GDP growth rates from 2013 to 2020 made by the Chinese Academy of Social Sciences (CASS) are employed as the benchmark. Considering the uncertainty involved in China's economic development, especially as China enters a "new normal", it is necessary to consider the possible impacts of different economic growth rates on coal consumption. Therefore, we consider two alternative GDP growth rates. In the second scenario, the average growth rate of GDP per capita between 2013 and 2020 is 20% higher than in the benchmark scenario, while in the third scenario, the average growth rate is 20% lower the benchmark. As a result, the second and third scenarios are named the "high growth" and "low growth" scenarios, respectively.

Because we utilize per capita GDP as an explanatory variable, the predicted provincial population should be used for the calculation of the per capita values. We use the predicted population data, including mortality and birth rates, from the World Bank. Considering the fact that variation of the population growth rate is not as large as that of the GDP growth rate, especially before 2020, we do not test alternative scenarios for the population growth rate.

In summary, the projected GDP growth rates and population indicators for the three scenarios are shown in Table 3.[12]

[12] It is generally believed that China's provincial statistics for GDP are quite flawed, while China's national statistics are more

Table 3 The forecast growth rates for the key explanatory variables under different scenarios.

Scenario	1 (benchmark)				2 (low growth)				3 (high growth)			
	2013	2014	2015	2016-20	2013	2014	2015	2016-20	2013	2014	2015	2016-20
Mortality rate	2.04	2.04	2.04	1.83	2.04	2.04	2.04	1.83	2.04	2.04	2.04	1.83
Birth rate	1.37	1.37	1.37	1.30	1.37	1.37	1.37	1.30	1.37	1.37	1.37	1.30
Aggregate Population growth rate	0.58	0.58	0.58	0.48	0.58	0.58	0.58	0.48	0.58	0.58	0.58	0.48
GDP per capita growth rate	7.74	7.30	7.00	6.50	6.16	5.84	5.60	5.20	9.24	8.76	8.40	7.80

Note: All figures are percentages.
Source: The GDP growth rates are from Economic Blue Book: China Economic Situation Analysis and Forecasting in 2015, published on 15th Dec. 2014. The population forecasts in the first three lines are from the World Bank Population Forecasting Report in 2010-2050 (http://datatopics.worldbank.org/hnp/popestimates, accessed on 28 April, 2015).

After the predictions of the key explanatory variables are made, China's provincial and national coal consumption can be forecasted. According to model 3, forecasts are made for each province and year. For example, in 2013, province i's coal consumption is forecasted by estimating model 3 using its projected GDP per capita for 2013, its own coal consumption in 2012 and the spatial factor $\sum_{j=1}^{k} w_{ij} \ln(CoCoperc_{j,t-1})$ calculated from all other provinces' coal consumption in 2012. After the coal consumption values for all provinces have been forecasted for 2013, the same procedure is employed to forecast provincial coal consumption for each remaining year in the 2014-2020 forecasting period. The projected national coal consumption is equal to the sum of the projected coal consumptions of all provinces. In

reliable (e.g., Wu, 2006; Chow, 2006). Because, in China, the GDP growth rate is usually considered one of the most important achievements of provincial and local governments, provincial officials have incentives to intervene in and even manipulate GDP growth rate statistics; therefore, for quite a long time, the sum of provincial GDP values has been higher than national GDP. To address this problem, we estimate provincial GDP by multiplying the national GDP statistics by the corresponding provincial GDP share, which is calculated using provincial statistics.

Figure 2, national coal consumption estimates for all three scenarios are plotted from 2013 to 2020.

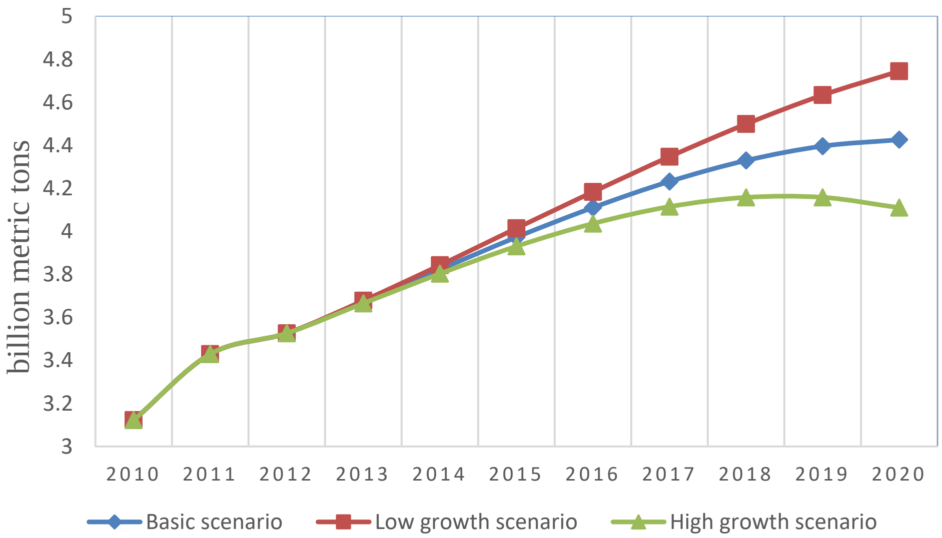

Figure 2. Projected National coal consumption from 2013 to 2020.

4. Discussion

4.1 Estimation Results for the Determinants of Coal Consumption

Several basic findings from the estimation results shown in Table 2 are listed as follows.

First, there is supporting evidence for the existence of an EKC for China's coal consumption. For all models, the estimated coefficients of GDP per capita are significant and positive, while the coefficients of its square term are significant and negative. These results suggest there is an inverted U-shaped EKC.[13] To some extent, this finding deepens the understanding of the relationship between China's energy consumption and economic growth. In previous studies, some researchers have verified the linear causality from coal consumption to economic growth in China (e.g., Bloch et al., 2012; Li and Leung, 2012). In a recent study, Zhang and Da (2015) found that although economic growth still proves the main contributor to coal consumption and CO_2 emissions, the relative decoupling effect between final energy-related CO2 emissions and economic growth in China has become increasingly apparent since mid-1990s. The findings of previous studies suggest that the actual relationship between coal consumption and economic growth in China might probably be nonlinear, which is confirmed by our estimation results. More concretely, the nexus between the two is proven inverted-U shaped. There are two possible explanations for the existence of an EKC for coal consumption in China. First, Chinese citizens may demand improved environmental quality, especially cleaner air, as economic development reaches a certain stage. Currently, serious haze and fog pollution frequently affect most of eastern and northern China, which has aroused the environmental awareness of an increasing number of Chinese people. Under increasing pressure from the public, the Chinese government has also begun to actively constrain the coal consumption that is most blamed for serious air pollution. Second, China's energy mix has begun to move in a cleaner direction. Although coal is still the dominant energy resource in China, its share of energy consumption has decreased from 76.2% in 1990 to 66.6% in 2012 (China Statistic Yearbook 2014). In several statements, China's government has vowed to continue reducing the ratio of coal consumption and to promote the usage of cleaner energy

[13] As a robustness check, we have tested specifications with cubic terms of GDP per capita, following Halkos and Paizanos (2013) and Hao et al. (2014). However, the estimated cubic term is insignificant for all methods, and we simply exclude the cubic term and report the results with the original and squared terms of GDP per capita, as shown in Table 2.

sources, such as solar and wind.[14] By changing its economic and industrial structures, China could improve its energy mix and decrease coal consumption even as total energy demand increases.

In addition, the positive coefficients of the spatial interaction term $\sum_{j=1}^{k} w_{ij} \ln(CoCoperc_{j,t-1})$ in models (3)-(8) indicate that the spatial correlation of China's coal consumption is positive and statistically significant. This finding is consistent with Cattaneo et al. (2011). Moreover, the positive spatial correlation in coal consumption explains, to a great extent, why peak coal consumption has not been reached. It should be noted that according to the estimation results of model (3), the benchmark model for the forecast, the theoretical turning point of the EKC occurs when per capita GDP reaches 4627 yuan (at constant 1978 prices). China's per capita GDP in 2012 had already 6545 yuan (at constant 1978 prices), and peak coal consumption has probably not been reached.[15] Because the turning point of the EKC is calculated purely based on the estimated coefficients of per capita GDP and its squared term, the theoretical turning point actually ignores the effects of all the control variables. The positive spatial correlation in coal consumption suggests that a province may be stimulated to consume more coal when it observes its neighboring provinces increasing coal consumption. Given the remarkably high estimated coefficient of the spatial integration variable $\sum_{j=1}^{k} w_{ij} \ln(CoCoperc_{j,t-1})$, the spatial correlation of coal consumption is sufficiently high to continue increasing coal consumption even after the theoretical turning point has been reached. There are several possible reasons

[14] The Chinese government has made repeated commitments to show its determination to improve China's energy mix by reducing coal consumption. Despite Beijing's statements during the 2014 APEC Summit that the share of non-fossil energy in China's energy consumption would reach 20%, the Chinese government's 2014 Work Report claims that by the end of 2014, China would eliminate outdated industrial capacity that consumes coal intensively, including 50000 inefficient coal burning boilers, 27 million tons of steel and 42 million tons of cement.

[15] The formal forecasts are conducted in section 6. Under the benchmark scenario and lower growth scenario, peak coal consumption in China does not occur before 2020.

for the existence of spatial dependence: (1) High coal consumption is usually driven by rapid industrialization and the development of heavy industries. Over the short- and medium-run, the rapid development of coal-intensive industries in one province may effectively foster its economic growth. Therefore, neighboring provinces have strong incentives to copy the development styles of that province, which may cause the coal consumption of the region to increase rapidly. (2) Because coal reserves in China are not evenly distributed, provinces with rich coal reserves and their neighboring provinces tend to develop coal-intensive industries. Take northern provinces of Inner Mongolia and Shanxi, for example. As major coal producers, it is more convenient for them to transport coal for coking to nearby provinces, such as Hebei and Liaoning. (3) As Maasoumi and Wang (2008) noted, development among different regions is so unequal that several convergence clubs within China may be observed. The provinces in each convergence club have similar industrial structures and economic development styles. As a result, provinces in the same convergence club may share characteristics of coal consumption; therefore, spatial correlation in coal consumption in these provinces may be significant (Poon et al., 2006).

Another important observation from the estimation results shown in Table 2 is the inertia in provincial coal consumption over time. Because the coefficient of the first lag of coal consumption $\ln(CoCoperc_{i,t-1})$ is significantly positive and relatively stable in magnitude (ranging between 0.7 and 0.9 for system GMM and LSDVC estimations), the coal consumption of one province is influenced heavily by its historical consumption.

Other control variables also have important impacts on coal consumption. For instance, because the estimated coefficients of *Second ratio* are significant and positive, a higher ratio of the secondary industry increases coal demand. Specifically, an increase in the share of secondary industry by one percent would cause coal consumption per capita to rise by approximately 1%, other things being equal. Similarly, the results suggest that urbanization is an important reason for the surge in coal consumption and related pollutant emissions.[16] This finding is in line with previous studies (e.g., Auffhammer and Carson, 2008; You, 2013). However, the coefficients of trade openness for the system GMM and LSDVC estimations are significant and negative (models 5 and 8 in Table 2), implying that the Pollution Haven Hypotheses (PHH) is not valid for China.[17]

4.2 The Dynamic Features of Projected National and Provincial Coal Consumption

As shown in Figure 2, the trend of China's coal consumption is increasing from 2013 to 2020. Only in the high growth scenario does national coal consumption peak, at approximately 4.16 billion metric tons in 2019. An interesting observation from Figure 2 is that the growth rate of coal consumption is higher when the GDP growth rate is lower. The main reason for this phenomenon is that the inverted U-shaped EKC exists and dominates the dynamics of coal consumption. When the economy grows at a higher speed, citizens demand environmental

[16] There are two possible explanations for the positive relationship between urbanization and coal consumption. First, during the process of urbanization, changes in lifestyle from traditional agricultural society to modern industrial society increase demand for energy use, especially from coal. For instance, many Chinese citizens still rely on coal for heating and cooking. Second, the gathering of population creates larger market for industrial products and stimulates the development of industries. Therefore, more coal-intensive factories and industries are built, and coal consumption increases.

[17] The Pollution Haven Hypotheses (PHH) claims that developed countries have incentives to transfer polluting industry to developing countries to evade strict domestic environmental regulations; therefore, the pollution in developing countries increases along with rapid increases in foreign trade. For more information about the PHH, one could refer to a series of studies on this topic, including Eskeland and Harrison (2003), Cole (2004), Kellenberg (2009) and Manderson and Kneller (2012).

improvement that increases pressure on energy-intensive and pollution-intensive firms to switch from dirty coal to other forms of energy. When the pressure to reduce coal consumption overwhelms the increase in coal demand caused by economic growth, coal consumption reaches its turning point and then begins to decrease. According to the system GMM estimation results shown in Table 2, the level of GDP per capita corresponding to the turning point of coal consumption has already been reached by some developed provinces, and the level will be reached by the majority of provinces as soon as the starting year of the forecasting period (2013). As a result, the faster per capita GDP grows, the sooner the peak of coal consumption will be reached.

Predicted national coal consumption is presented in the last row of Table 4. A simple calculation suggests that national coal consumption increases at a decreasing speed under the benchmark scenario. The national annual growth rate of coal consumption decreased from 16.9% from 1995-2012 to approximately 2.7% from 2013-2020. Moreover, for the 2018-2020 period, projected coal consumption will increase only slightly, an annual growth rate of 1.11 percent. As a result, under the benchmark scenario, China’s coal consumption peaks soon after the year 2020.

Table 4 Forecasts of provincial and national coal consumption from 2013 to 2020 under the benchmark scenario (million metric tons).

Province	2013	2014	2015	2016	2017	2018	2019	2020
Beijing	20.12	21.63	22.83	23.65	24.09	24.11	23.71	22.92
Tianjin	37.17	32.29	28.03	24.27	20.96	18.02	15.41	13.09
Hebei	267.64	280.33	291.05	299.16	304.52	306.76	305.59	300.84
Shanxi	276.46	273.95	271.24	267.75	263.41	257.89	250.96	242.43
Inner Mongolia	258.25	226.84	200.18	177.03	156.75	138.70	122.43	107.63
Liaoning	146.13	143.53	139.51	134.09	127.50	119.87	111.36	102.16
Jilin	95.05	99.37	102.35	103.83	103.82	102.31	99.35	95.02

Heilongjiang	125.82	137.61	147.74	155.67	161.19	164.04	164.08	161.29
Shanghai	38.01	31.42	26.00	21.51	17.78	14.66	12.04	9.83
Jiangsu	207.08	190.78	175.29	160.39	146.10	132.31	119.00	106.15
Zhejiang	117.57	117.96	117.29	115.48	112.61	108.68	103.73	97.83
Anhui	134.05	149.56	164.99	179.77	193.56	205.88	216.21	224.05
Fujian	72.32	75.58	78.21	80.07	81.13	81.29	80.51	78.74
Jiangxi	65.42	76.68	88.55	100.65	112.73	124.40	135.23	144.77
Shandong	329.98	332.43	332.25	329.07	323.04	314.08	302.20	287.51
Henan	228.72	253.65	278.07	301.05	322.07	340.34	355.09	365.58
Hubei	138.17	147.99	156.85	164.34	170.32	174.51	176.67	176.62
Hunan	112.96	128.89	145.03	160.83	175.92	189.77	201.81	211.52
Guangdong	149.49	155.48	160.30	163.67	165.52	165.67	164.01	160.46
Guangxi	67.92	78.07	89.04	100.59	112.59	124.74	136.71	148.09
Hainan	8.85	10.27	11.78	13.32	14.88	16.39	17.81	19.07
Sichuan	172.58	195.17	217.67	239.25	259.40	277.35	292.34	303.66
Guizhou	115.93	125.12	135.13	145.65	156.59	167.70	178.65	189.07
Yunnan	90.13	102.15	115.68	130.54	146.73	164.05	182.19	200.74
Shaanxi	133.72	139.47	144.54	148.62	151.64	153.40	153.73	152.48
Gansu	60.38	68.09	75.97	83.77	91.36	98.47	104.86	110.26
Qinghai	16.82	18.66	20.49	22.25	23.90	25.38	26.65	27.64
Ningxia	63.59	62.69	62.20	61.90	61.74	61.59	61.34	60.88
Xinjiang	121.23	147.18	174.47	202.26	230.01	256.98	282.42	305.55
National	3671.54	3822.88	3972.74	4110.44	4231.83	4329.37	4396.09	4425.88

Considering the sizeable development differences among regions in China, the projected dynamics of coal consumption might vary remarkably by province. In table 4, provincial coal consumption between 2013 and 2020 predicted by the benchmark scenario is also presented. Under the benchmark scenario, some relatively developed provinces will reach the turning point in coal consumption before 2020 (e.g., Beijing in 2017, Guangdong in 2018), while most of the remote, developing western provinces (such as Guizhou, Yunnan and Gansu) will experience relatively rapid growth in coal consumption. According to the forecast, the provinces can be divided into three categories based on the dynamic characteristics of projected coal consumption.

For the first group of provinces, coal consumption continues to decrease from 2013 to 2020. For these provinces, peak coal consumption appeared before 2013; therefore, a steady downward trend in coal consumption is expected. Provinces in this group include Shanghai, Tianjin, Inner Mongolia, Jiangsu, Liaoning and Zhejiang. An illustration of the projected coal consumption of Shanghai under the three alternative scenarios is drawn in Figure 3. The turning point in coal consumption in Shanghai appeared in 2011, and afterwards, coal consumption decreases over time.

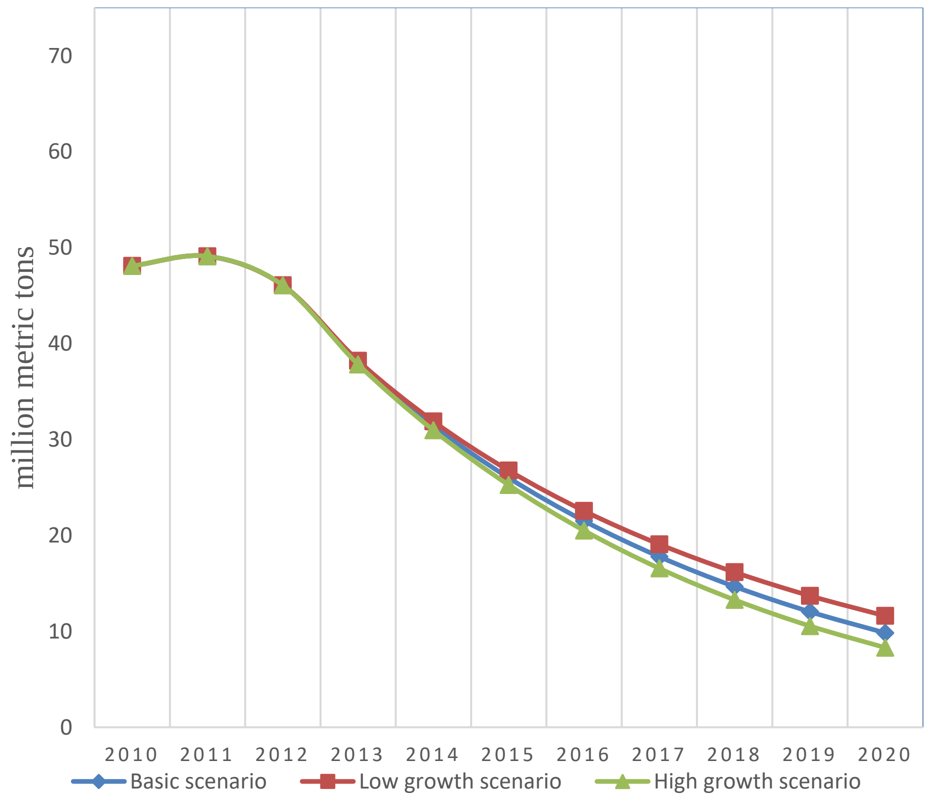

Figure 3. Projected coal demand of Shanghai

For the second group, coal consumption during the 2013-2020 forecasting period is expected to remain approximately stable. For these provinces, the turning point in coal consumption may occur during this period; therefore, the variation of coal consumption around the turning point is not significant. The provinces in this group include Fujian, Hebei, Ningxia, Guangdong, Jilin, Beijing, Shanxi and Shandong. For these 8 provinces, provincial coal consumption varies moderately between 2010 and 2020: under the benchmark scenario, the average annual growth rate of coal consumption varies from -2.6% to 1.1%. For example, the projected coal consumption scenarios for Fujian are plotted in Figure 4. For Fujian province, coal consumption is projected to peak around 2013 under the benchmark scenario, and then, it should slowly and steadily decrease.

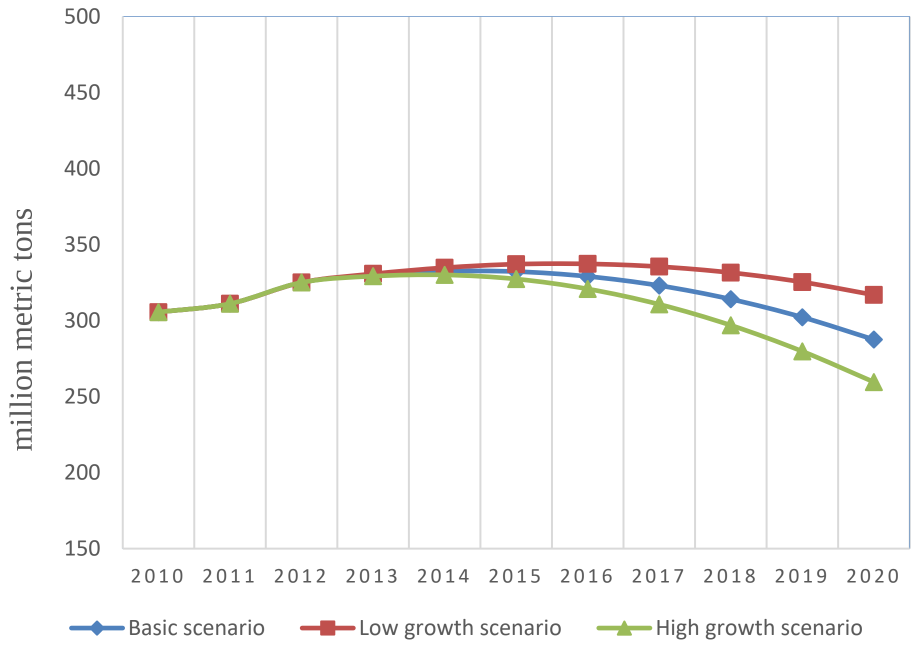

Figure 4. Projected coal demand of Shandong

For the third group, coal consumption is projected to rise continuously from 2013 to 2020 with no peak being reached. The provinces in this group include Xinjiang, Hainan, Guangxi, Jiangxi, Qinghai, Yunnan, Gansu, Hunan, Guizhou, Sichuan, Anhui, Henan, Heilongjiang, Hubei and Shaanxi. In these provinces, Xinjiang would experience the fastest increase in coal demand and an annual growth rate of 13.5%, while Shannxi has lowest annual growth rate of 3.1%. The predicted coal consumption of Guangxi under the three alternative scenarios is depicted in Figure 5. As shown clearly in Figure 5, the increase in coal consumption in Guangxi is remarkable: under the benchmark scenario, its coal consumption would reach approximately 150 million tons, approximately 3 times its consumption in 2010. Note that in 2012, Guangxi's per capita GDP was only 4499 yuan (at 1978 constant prices), which is considerably lower than the national average (6545 yuan at 1978 constant prices). Therefore, the growth effect dominates the dynamics of coal consumption in Guangxi, and coal consumption should increase rapidly as the economy continues to develop.

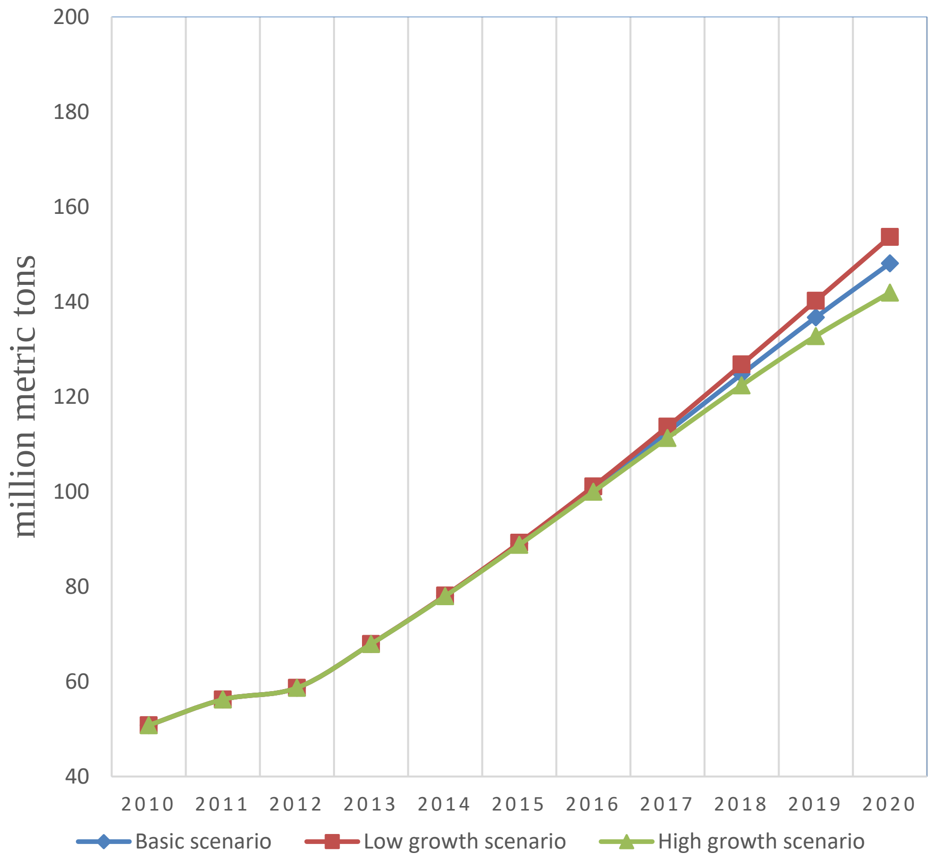

Figure 5. Projected coal demand of Guangxi

Now that Chinese provinces are expected to experience different patterns of coal consumption in the foreseeable future, it is interesting and meaningful to dig deeper to explore the reasons why the different projections of coal consumption may occur. To sum up, there are mainly three reasons as follows.

First of all, there exists remarkable regional development gap among the provinces in China. Some western provinces, including Gansu, Xinjiang and Qinghai, have remained at the bottom of the ranking list of per capita GDP. For instance, according to China Statistical Yearbook 2014, in year 2013, per capita GDP of Gansu, one of the least developed western provinces, was around 24,296 yuan; while that number for Beijing city was 93,213 yuan, nearly four times of Gansu's level. Given the existence of the inverted-U shaped EKC relationship between energy consumption and GDP per capita in China, the provinces with lower level of GDP per capita (such as Gansu, Qinghai and Guizhou) would experience rapid increase in coal consumption as the economy continues to grow, while the relatively prosperous provinces (including Shanghai and Zhejiang) whose per capita GDP has already far exceeded the turning point of coal consumption are expected to consume less and less coal over time.

Secondly, the substantial differences in industry structure among provinces are also responsible for the differences in the patterns of coal consumption projections. According to the estimation results shown in Table 2, the coefficients of the ratio of second industry value-added to GDP are stable and considerably large in magnitude for all three estimation methods, ranging from 0.83 to 1.07. As a result, because the importance of the energy-intensive second industry differs across provinces, the forecasted coal consumption may also differ. For instance, in the megacities of Beijing and Shanghai, the tertiary industry plays the most important role in economic development, while the share of the second industry has reduced to be less than 40%. Therefore, the projected coal consumption for these regions would start decreasing before 2020. However, in some less-developed central and western provinces (such as Qinghai, Sichuan and Henan), the ratios of second industry value-added to GDP were above 50% in 2012 (that ratio of Qinghai even reached 57% in 2012). The heavy reliance on the second industry may cause the forecasted coal consumption in these provinces to increase in the near future.

Thirdly, due to the significant spatial correlations in coal consumption among adjacent provinces, the positive spill-over effects of a province with high forecasted coal consumption may cause its neighboring provinces' projected coal consumptions to increase remarkably. As an illustration, the expected rapid increase in coal consumption in some of the central and western provinces could be partly attributed to the significant and positive spatial effects of coal consumption among these provinces. It is noteworthy that Qinghai, Yunnan, Gansu, Hunan, Guizhou, and Shannxi share provincial boundaries with Sichuan, and these provinces have similar industrial structure and energy mix. As a result, the positive spatial effects in coal consumption among these provinces, induced by relatively short geographical distance and similar economic characteristics, would probably affect each other and provide intensives to increase coal consumption once anyone of these provinces intends to consume more coal.

5. Conclusions and Policy Implications

This study utilizes panel data for 29 Chinese provinces from 1995 to 2012 to investigate the determinants of coal consumption in China, and forecasts of coal consumption for 2013-2020 are conducted based on the estimation results. Using different estimation methods, this study verifies the existence of an Environmental Kuznets Curve (EKC). Moreover, by incorporating a spatial integration term, we also find evidence for strong spatial correlation in Chinese provincial coal consumption. Moreover, other socio-economic determinants, such as the importance of secondary industry, urbanization and trade openness, are found to be significantly related to China's coal consumption.

Judging from the RMSFE and AMSFE values, we chose an intensive-form specification of the system GMM estimations to conduct the out-of-sample forecasts. To capture the influences of possible variation in economic growth rates on the dynamics of coal consumption, three alternative growth rates of per capita GDP are considered in the predictions. According to the forecast results, under the benchmark scenario, China's coal consumption would continue to increase through 2020 (when coal consumption will reach 4426 million metric tons), but the growth rate should decrease over time. Only under the rapid growth scenario is China's coal consumption projected to peak before 2020. Thus, although China will consume a considerable amount of coal over the foreseeable future, it will not take long for China to bid farewell to its rapid coal consumption growth rate.

Based on these estimations and forecast results, several conclusions and policy implications follow.

First, because there is competition across provinces for higher economic growth rates, spatial correlation in coal consumption stimulates provinces to consume more coal. The spatial effects are so remarkable that they dominate recent coal consumption, as the theoretical turning point of the EKC for coal consumption has already been reached. As a result, such spatial effects deserve considerable attention from the Chinese government. To achieve its goal of reducing coal consumption, the government could utilize the characteristics of spatial correlation by encouraging provinces with high coal consumption to reduce their consumption. For instance, specific rewards or bonuses could be given to provinces that actively reduce coal consumption, and some representative areas of low coal consumption could be established. Due to the existence of spatial correlation in coal consumption, the first-movers in reducing coal consumptions would have significant demonstration effects on their neighbors, and these provinces may then compete to decrease coal consumption.

Second, because there is evidence for the existence of an EKC for coal consumption in China, a reasonable economic growth rate is needed to improve the energy consumption structure and environmental quality. According to the forecast, the expected growth rate of coal consumption is lower when the GDP growth rate is higher, and the consumption peak occurs only when the predicted per capita GDP growth rate between 2013 and 2020 is the highest of the three alternative scenarios. As a result, although China’s economy has entered a “new normal” state of moderately fast economic growth rate, caution should be exercised to prevent China’s growth rate from decreasing too rapidly. Maintaining a reasonable and sustainable growth rate in China is vital not only for promoting the welfare of its people but also for improving the environment over the long run.

Third, other factors may also affect coal consumption significantly. These factors include the share of secondary industry, urbanization rate and trade openness. We have also found that coal consumption has heavy inertia: current provincial coal consumption is highly dependent on its historical consumption. In other words, coal consumption exhibits strong path dependence. As a result, the government should take into consideration all these determinants when formulating regulations and policies to constrain coal consumption. For instance, the industrial structure should be improved by prompting the development of tertiary industries and reasonably reducing the share of secondary industries. According to the statistics of the China Information and Industry Department, secondary industry accounts for approximately 70% of energy consumption, most of which is coal. Hence, adjustment of the industrial structure in favor of tertiary industry could sufficiently decrease coal consumption. Considering the inertia of coal consumption, early action is important to restrain coal consumption over the long run.

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