Industrial Coal Demand in China: A Provincial Analysis

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Summary

In recent years, concerns regarding the environmental implications of the rising coal demand have induced considerable efforts to generate long-term forecasts of China's energy requirements. Nevertheless, none of the previous empirical studies on energy demand for China has tackled the issue of modelling coal demand in China at provincial level. The aim of this paper is to fill this gap. In particular, we model and forecast the Chinese demand for coal using time series data disaggregated by provinces. Moreover, not only does our analysis account for heterogeneity among provinces, but also, given the nature of the data, it captures the presence of spatial autocorrelation among provinces using a spatial econometric model. A fixed effects spatial lag model and a fixed effects spatial error model are estimated to describe and forecast industrial coal demand. Our empirical results show that the fixed effect spatial lag model better captures the existing interdependence between provinces. This model forecasts an average annual increase in coal demand to 2010 of 4 percent.

Keywords: Energy demand, Coal demand, China, Spatial econometrics, Panel data, Forecasting

JEL Classification: C23, E6, Q31, Q41

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1. Introduction

The exceptional economic development of China has been traditionally the central issue for theoretical as well as applied economists, who are interested in finding and explaining the cause of such a explosive economic growth. The key ingredients of the Chinese economic performance have been deeply analysed, in order to understand China's potential and its future directions. Only recently however, the interest shifts toward the analysis of the implications of such spectacular development, in particular concerning the impact on the world energy economy.

China since the onset of economic reforms has shown sustained economic growth at an average annual rate of 9.5 percent: this enabled the country to increase by more than 10 times both total GDP and per capita GDP during this period (WDI, 2006). This surge emerged after the central government set in 1978 the basis for shifting the system toward a socialist modernization and toward a revitalized domestic economy, open up to outside word.

This expansion however, along with a massive industrialization, urbanization and motorization, induced a substantial increase in energy consumption. In 2004 for example, the rate of growth of energy consumption reached 18.3 percent (APERC, 2007) and the actual levels make China the largest energy user in Asia and the second largest in the world, after only USA. China's energy structure has been traditionally dominated by coal, given the abundance of coal mines located in the country. For example in the half of 20th century coal was nearly the sole fuel for energy production in China, while currently other fuels enter the energy mix. Nevertheless, the share of coal remains extremely high, largely dominating the energy scenario.

A big share in demand is absorbed by the heavy industry, which accounts for more than 80 percent of total final energy consumption. China in fact is characterized by an exceptionally high share of valued added in industry and a low share in services. A main challenge for China therefore, remains the rebalance of the economy, through a relative shift from industry-led growth toward more services-led growth as well as a more labour intensive urban growth. This change will allow not only to balance the path of development, aligning China to the economic structure of the industrialized countries, but also to save energy and resources and to protect the environment. In fact the continued industry led expansion requires more energy and puts heavy burden on the environment, inducing a non-sustainable growth over the longer horizon. Although the effort is placed to forge a sustainable energy path, which eventually substitutes more efficient fuels for coal, this fuel will remain the greatest energy input.

In recent years, concerns regarding the environmental implications of the rising energy demand, induces considerable efforts to generate long term forecasting of China's coal requirements. The economic analysis, which are all conducted at the country level, are almost unanimous in projecting increasing trend in coal demand. To our knowledge, however, no prior study models the coal demand in China at provincial level and produces future forecasting. The availability of a data set at provincial level allows us to fill in the current gap in research. The aim of this paper is to analyse the Chinese industrial coal demand using a panel disaggregated by provinces: this allows us to account for the heterogeneity between provinces. Moreover, given the nature of the data, the spatial autocorrelation between provinces will be captured, using a spatial econometric model. The remainder of the paper is organized as follows. Section 2 presents a brief review of the literature on energy consumption in China. Section 3 outlines the methodology adopted. Section 4 describes the data set used and analyses the overall energy background in China. Section 5 identifies potential sources of spatial interaction among provinces. Section 6 presents the econometric results while Section 7 displays forecasting. Finally, Section 8 contains summary and conclusions.

2. Literature review

The empirical literature which attempts to modelling the energy demand in China has shown two distinct goals. One is the estimation of long run income elasticity of energy demand, generally based on time series techniques such as cointegration and vector error-correction, as well as the provision of energy demand forecasts. A second one is the detailed analysis of the factors responsible for the energy intensity decline experienced by China during the ongoing extraordinary economic development. This latter goal is achieved through econometric model which decomposes the contributions of variables such as sectoral shift or subsector productivity change to total energy use.

Among the first group can be cited Masih and Masih (1996), who employ the dynamic OLS procedure developed by Stock and Watson using annual data from 1953 to 1992. The advantage of this methodology is that it allows to account for both the endogenous nature of the regressors, as well as for the non-stationarity of the series used in modelling demand functions in a time series context. Controlling for the simultaneity bias between coal demand and its determinants, the authors report absolute long run elasticities, for both price and income, close to unity for China. Demand for coal modelling and forecast is provided as well by Chan and Lee (1997), who use data from 1953 to 1994. Applying the Engle-Granger's error correction model, which include price, income as well as a structural shift as regressors, the authors report long-run elasticities slightly lower than unitary, suggesting a less than proportionate reaction of coal demand to income and price changes. They finally predict a rise for coal consumption from around 1.2 billion tons in 1994 to a level of 1.48

billion tons in 2000 as a consequence of a ten per cent average increase in national income, together with a four per cent annual increase in real coal price and a one per cent drop in share of heavy industry's output in national income. A less than unitary GDP elasticity for electricity demand is reported in Lin (2003) through a vector error correction model for the period 1975-2001. It should be noted that, extending the sample period to the prior PRC's reforms phase, the elasticity becomes larger but still lower than one. Moreover, according to the author, the electricity demand rates are projected to grow by 5.8 percent on average between 2002 and 2010. This prediction indicates a remarkable decline in the consumption growth rate if compared with its historical trend, which averaged 9 percent in the period 1978-2001.

Crompton and Wu (2005) propose an alternative methodology to forecast energy consumption in China, applying a Bayesian vector autoregression (BVAR). This methodology avoids the problem of overparameterization, typical of VAR models with large number of lags. With a sample period ranging from 1956 to 2003, they forecast over the period 2004-2010 an average 3.8 per cent rise in total energy consumption and a 3.3 per cent increase in coal demand. Adams and Shachmurove (2007) apply an energy balance framework to model energy functions in China. This methodology is traditionally used as an accounting system to investigate energy supply and utilization, but the authors employ it to provide energy demand prospects for 2010 and 2020. Econometric estimation of the linkage parameters suggests an income elasticity for fuel consumption varying between 0.5 and 0.6. The size of the parameter, which is sensibly lower than one, reflects eventually some ongoing improvements in the use of energy or alternatively a shift toward products which are less energy-intensive. Moreover, the authors conclude that there must be a substitution of more efficient fuels for coal given that they predict a decrease in coal demand of six percent, despite the increase in final energy consumption of 2.6 percent.

In a cross section context, Tang and La Croix (1993) analyse the impact of economic activity on total energy consumption in China, using pooled cross section data at province level for the period 1985-1989. They report income elasticity for total energy around one, which is lower than the coefficient estimated with a similar methodology for developing countries. In fact, Zilberfarb and Adams (1981) and Reister (1987), applying pooled cross section data for developing countries, find that the income elasticity is significantly greater than one and is stable over time. Tang and La Croix suggest that a unitary elasticity implies a constant energy intensity for Chinese provinces along the process of economic development.

A different beliefs, regarding the trend in energy intensity in China, is shared by a strand of empirical literature, which notes a decline in energy consumption per unit of GDP, despite the increase in total energy consumption. The objective of these papers, which include among others

Kambara (1992), Garbaccio et al. (1999), Chu at al. (2006), is to investigate the explanation for such decline in energy intensity. The authors conclude that technical and structural changes are responsible for the improved efficiency in China. Moreover, applying disaggregated firm-level data, Fisher-Vanden et al. (2004) state that nearly half of the decline in energy intensity is due to gains in efficiency at firm level, which may involve the development of new materials.

3. Methodological approach

The main feature of spatial models is the introduction of some forms of interactions within agents, who are influenced in their choices by other agents rather than behaving in isolation. In particular, given the geographical component of these models, the concepts of location and spatial externalities are widely used.

The existence of such interactions generate the so called "spatial dependence": in general, this term refers to the presence of a functional relationship between what happens at one point in space and what happens elsewhere (Anselin, 1988). In the modern economic theory, a spatial approach can be found in the new economic geography, as embodied, among others, in the works of Krugman (1991, 1996). These models try to explain the concentration of production by means of increasing returns, path dependence and imperfect competition, which determine spatial externalities and spillovers. Given the existence of such spatial interactions, an empirical analysis of these models requires a spatial econometric approach.

A classical economic framework, where total costs are minimized subject to a production function, generates the following industrial coal demand:

$$C_{it} = R(Z_{it}) \tag{1}$$

where C_{it} is the coal demand in province i at time t and Z contains all standard factors that influence demand, such as input prices and output. However, it may the case that the demand function depends also on a strategic-interaction term, represented by the coal demand in other provinces. If historically, the coal-fired power stations were built close to mines to reduce the transportation costs, subsequent firm may have located in the same area. This choice could be made to benefit from pecuniary externalities, generated by the existence of coal-specific infrastructure, such as installed grids for power transfer. This implies that the coal-based energy sector concentrates where other energy producing firms are located, which reflects the areas with good access to the fuel input, rather than the area most industrialized. If this is the case, standard demand determinants cannot fully explain the industrial coal demand, but spatial interaction term should enter the analysis.

The difficult task in spatial model is to correctly incorporate the form of spatial dependence: there are two main sources of complexity. First of all, contrary to the time series analysis, where the time structure univocally determines the correlation between observations, in spatial analysis the definition of the dependence is fairly arbitrary. For example, the geographical space may not be considered in its narrow physical dimension but it can be extended to include concepts of social space and social capital; moreover, the distance metrics employed does not limit to the standard Euclidean, but social distance or economic distance can be reasonably introduced. Therefore, the estimation of spatial functions requires the identification of which locations are neighbours applying a spatial weighting matrix: however, given the arbitrariness explained above, the weigh matrix can be modelled according to multiple criteria.

The second complexity depends on the way the spatial dependence is specified in the regression model. In fact the spatial correlation can take the form of spatial lag or spatial error (Anselin, 1988): in the first case, the inclusion of a spatial dependent variable is required. Applying panel data, the model becomes:

$$C_{it} = \rho W C_{it} + Z_{it}^{'} \beta + \mu_i + \varepsilon_{it} \tag{2}$$

where ρ is the spatial autoregressive parameter, and W is the spatial weight matrix, which defines the structure of the dependence among the local units of observations, such as the provinces.

In the second case, a spatial process for the disturbance terms should be specified:

$$\begin{aligned} C_{it} &= Z_{it}^{'} \beta + \mu_i + \varepsilon_{it} \\ \varepsilon_{it} &= \lambda W \varepsilon_{it} + v_{it} \end{aligned} \tag{3}$$

where λ is the spatial autoregressive coefficient. A bit of manipulation in equation (2) leads to:

$$C_{it} = (I - \rho W)^{-1} Z_{it}^{'} \beta + (I - \rho W)^{-1} (\mu_i + \varepsilon_{it}) \tag{4}$$

The matrix inverse $(I - \rho W)^{-1}$ is a full matrix which induces error terms in all locations (Anselin and Bera, 1998). It follows that this simultaneity should be accounted for applying a maximum

likelihood estimation or an instrumental variable framework. Given the presence of simultaneity, in fact, the OLS estimation would be biased and inconsistent.
In the case of the spatial error, the arrangement of equation (3) produces:

$$C_{it} = Z_{it}^{'}\beta + \mu_i + (I - \lambda W)^{-1} v_{it} \quad (5)$$

This regression fails the standard condition of spherical error terms, as the error covariance matrix contains non-constant diagonal elements. Therefore, the existence of spatial dependence in the disturbances induces hetheroskedasticity in ε irrespective of the covariance structure of v. The nuisance related to the spatial error dependence introduces a problem of inefficiency in the estimated parameters[1] and again maximum likelihood estimation is called for.

4. Data description

The dataset employed for this analysis is taken from the China Energy Databook (2004), published by the China Energy Group of the Lawrence Berkeley National Laboratory. The dataset collects important statistical information, drawn from national as well as provincial energy balances. Among other, the databook reports information on energy production, energy consumption, disaggregated for energy types, sectors and uses. Moreover, it offers macroeconomic indicators, such as Gross Domestic Product and Gross Output Value, and population indicators, such as population counting.
Of particular relevance for this analysis is the total industrial coal demand, which embodies the industrial energy consumption, the industrial non energy use as well as the consumption lost during the process of energy conversion. For China, the demand for coal in the industrial sector absorbs a considerable share of the aggregate volume and this share has slightly increased over time, as reported in the China Energy Databook (2004). In fact, the industrial sector is responsible for 85 per cent of total demand in 1995 and more than 90 per cent in 2002. Therefore industry is the primary driver for coal demand.
A second important feature is the relevance of coal as a source of energy. This fuel in fact is extremely abundant in the country and this makes China the larger producer and consumer of coal in the world. The China Energy Databook (2004) reports the composition of the primary energy demand, by fuel source: coal represents the key component of energy demand, accounting for over

[1] Anslein and Bera (1998) interpret the spatial error dependence as a nuisance induced by the spatial autocorrelation in measurement errors or in variables that are not crucial to the model, such as ignored spillovers across the units of observation.

60% of the primary energy consumption mix, followed by oil, hydro-power and natural gas. The importance of coal slightly decreases during time but this fuel still remains the undisguised driver of primary energy.

Regarding the composition of output value, China shows great unbalances, as far as it is characterized by an exceptionally high share of value added in industry and an exceptionally low share in services. This feature holds true not only comparing China to United States and Latin America, but also to the levels predicted by its basic characteristics. For example, industry is sometimes five times as large as the second bigger sector, which is agriculture (China Energy Databook, 2004).

This preliminary overlook of the Chinese economic and energy situation makes use of aggregated indicators provided by the data set. It should be noted, however, that the same information is as well available at provincial level: this feature allows us to study the Chinese energy demand through using a panel dimension, in order to account for the heterogeneity between provinces.

Concerning the administrative structure, China is composed by 22 provinces, five autonomous regions, four municipalities, and two special administrative regions. Unfortunately, for some of the territories, the data set offered incomplete information: to form a balanced structure, therefore, only 27 administrative units have been selected. Moreover, the provincial energy balances are accessible from 1995 to 2002 on yearly frequency. This makes a panel of 216 observations.

5. Source of provincial interactions

The structure of the generating capacity in China varies enormously from region to region and it is influenced by the location of the major sources of energy: hydropower plans, for example, are mainly located in the central and south China, whereas the thermal-power plans can be found in the north and north-east regions where coal is abundant (IEA, 2006).

FIGURE 1 HERE

China owns substantial reserves of conventional energy resources, but coal largely dominates the other energy inputs: in fact, China possess extensive coal reserves, which make the country the world's largest coal producer. Moreover, the coal reserves are highly geographically concentred as the two-thirds of the reserves are located in the northern provinces. The black circles in Figure 1 indicate the site of the top major coal mines, which supply more than 10 million tonnes per annum: the map shows that these mines are concentrated in eight provinces, all placed in the north-east and north regions. Table 1 reports the exact production of the mines in 1996: among others, Daton in Shanxi produces more than 30 million tonnes alone, while Kailuan in Hebei and Pingdingshan in Henan supply more than 17 million tonnes.

TABLE 1 HERE

Regarding the power generation, it should be noted that the ten major energy producing provinces, which use coal as an energy source are those at close distance from the major coal mines zones, described above. As published in the China Energy Databook (2004), these are: Shanxi, Shandong, Inner Mongolia, Henan, Hebei, Anhui, Heilongjiang, Shaanxi, Sichuan and Liaoning. This indicates that the power generation industry is concentrated in few inland provinces: coal-fired power stations are built at close distance from the mines, despite the largest centres for energy demand are located in the industrialized coastal areas. This correspondence is eventually due to transportation constraints, as the Chinese inland coal transport infrastructure, through which more than one half of total coal supply is moved, are inefficient and highly congested. On the contrary, there has been a great effort in increasing the energy transfer capacity from the country's resource rich areas to the high energy demanding regions: in fact, about 40 percent of total investment in the power sector are represented by transmission investment.

Finally, Table 2 reports the major ten provinces demanding industrial coal and again they reflect the position of the coal mines. This analysis suggests that the location of the energy source eventually plays an important role in explaining the industrial coal demand and therefore, interdependence between close by provinces can arise[2]. In particular, this may justify a form of interdependence, where the coal demand of province i is a function of coal demand in province j.

TABLE 2 HERE

It is important to note that, although the demand for industrial coal includes both energy and non-energy use of coal, the latter holds only a marginal role. In fact, the fraction of coal employed for the production of energy over total industrial use is stable around 99 percent during the sample period. This allows us to analyse the industrial coal demand following the described spatial structure, which is largely based on the link between coal mines, power generation and demand for

[2] Despite the extensive coal reserves available, China is increasing the volume of imported coal, in particular to meet the energy demand in the coastal provinces. The existence of a large fraction of coal imports in the Coastal area could weaken the hypothesis of pecuniary externalities available in the coal reserve zone. However, the provincial energy balance shows the in the 1995-2002 period the relevance of imports was minimal, and some of the provinces demanding imported coal were not located in the coastal region.

coal.

As a first instance, to investigate the spatial autocorrelation in the industrial coal variable, a simple picture showing the quintile distribution of the industrial coal demand can be reported. As it is shown in Figure 2, a cluster of high values can be identified in the North-East regions, in proximity to the coal mines zone, whereas a cluster of low demand is located in the Western area.[3] In fact, the five provinces demanding on average more than 70 million tonnes of coal are displayed in dark black and are concentrated in a bounded zone. Conversely, the five provinces demanding less than 20 million tonnes look slightly more dispersed, though three of them are neighbours. These provinces can be identified by the white colour.

FIGURE 2 HERE

The presence of spatial correlation between the units of observations can be further detected through a test which captures the extent to which values similarity matches with locations similarity. In particular, the coal demand can show positive spatial correlation if likewise values tend to cluster in space, or it can display negative correlation whenever the locations are surrounded by neighbour with dissimilar values. Finally, a zero spatial correlation implies that it is not possible to identify a specific spatial pattern of coal values. There are a number of widely used statistics which detect autocorrelation within the sample as a whole: for this reason they are defined global measures. These statistics represent a sort of covariance in connecting locations relative to the variance across locations. Among the global measures are the Moran's *I* statistics:

$$I = \frac{N}{S_0} \sum_i \sum_j w_{ij} z_i z_j \, / \sum_i z_i^2 \tag{6}$$

and the Geary's *c* statistics:

$$c = (N-1) \sum_i \sum_j w_{ij} (x_i - x_j)^2 \, / \, 2(S_0) \sum_i z_i^2 \tag{7}$$

with $z_i = x_i - \mu$, $S_0 = \sum_i \sum_j w_{ij}$ and where w are the single elements of the weight matrix W. As suggested, the choice of the weighting matrix can be determined according to alternative criteria. In

[3] Given the panel dimension of the observations, the variable employed is a 8 years average of the coal demand.

this analysis three different rules are applied. In the first matrix (W1) the neighbourhood set is defined according to common borders: $W = \{\omega_{ij}\}$, where $\omega_{ij} = 1$ if province i and j have common border and zero otherwise. It should be noted that to facilitate interpretation, the weight matrix is often standardized, letting the row elements sum one. Therefore $w_{ij} = \frac{\omega_{ij}}{\sum_{j=1}^{J} \omega_{ij}}$. The second matrix (W2) is based on a distance decay function, where $\omega_{ij} = 1/Dist_{ij}^2$, where $Dist_{ij}$ equals the Euclidean distance between province i and j, if $Dist_{ij}$ is less than 600 Km and 0 otherwise. In the third case (W3), the standardized matrix is computed setting $\omega_{ij} = 1$ if provinces i and j share a common major coal mine and 0 otherwise. We define a major coal mine, a mine that produces more than 10 million tonnes of coal and we identify the common neighbourhood as the circle space confined within an area of 300 km from the capital of the provinces.
A spatial clustering of high/high or low/low values results from $I>-1/(n-1)$ and $c<1$, whereas a negative spatial autocorrelation implies that $I<-1/(n-1)$ or $c>1$.

TABLE 3 HERE

An alternative way to measure the value similarity between one location and its neighbourhood set is offered by the local statistics. These local indicators offer association coefficients for each particular location: therefore, they produce an index of autocorrelation for each single location. A widely used local measure is the local Moran, which differs from the global counterpart in that it is based on a single summation rather than a double sum. In fact it disaggregates Moran's I into contributions for each location:

$$I_i = z_i \sum_j w_{ij} z_j \tag{8}$$

Table 3 and 4 report the value of the global measures applying the full set of matrixes along with the test statistics and its significance value[4]: there is no clear evidence of particular global spatial autocorrelation. In fact, the Moran’s I and the Geary statistics cannot depict an uniform picture regarding the structure of the global autocorrelation. In fact, the Geary’s c statistic detects a statistically significant correlation in one case only, whereas the Moran’s I rejects the null

[4] The test assumes that the distribution of the statistic is approximately normal

hypothesis of no spatial correlation in all cases. The sign of the statistics indicates the tendency toward a positive autocorrelation, but overall this result is quite frail.

TABLE 4 HERE

Turning to a local analysis, Table 5 reports the local Moran statistic, computed applying the same set of weight matrixes. Four provinces - Hebei, Shanxi, Shandong and Henan - reveal positive and significant spatial correlation and the result holds irrespective of the matrix applied. The interesting feature is that the locations which match the high values of their neighbours, are located in the north, which covers part of the coal mine area. A positive statistic, in fact, indicates that the four provinces not only own high coal demand but they are surrounded by locations with high coal demand. This finding suggests that the spatial autocorrelation exists, but it is not a global phenomenon. In fact, the presence of spatial correlation essentially turns up in isolated clusters.

TABLE 5 HERE

6. Empirical results and tests

To account for possible spatial autocorrelation, equations (2) and (3) are estimated applying Maximum Likelihood Estimation (MLE). The dependent variable is the provincial level industrial coal demand (*C*), which includes industrial energy demand, industrial non energy demand and the consumption lost during the process of energy conversion. According to the standard economic theory, the determinants of input factors are the level of production, proxied by real gross value added (RGVA) and input prices. Unfortunately, the latter variable is not available for China at provincial level, and notwithstanding we are aware of the big limitation, the econometric analysis has been conducted without this important control. It should be noted, however, that the price system in China has been highly regulated, and despite the ongoing deregulation, the strength of the impact of prices should be limited and less significant as in a market economy (Chu et al. 2006). For example, until 2002 the price of coal for energy generation, was set below market values as it was established by the central government authorities at the Annual Coal Procurement Conference. Moreover, in the power sector, the chance to switch to alternative fuels is limited given that the coal-fired energy generation is extremely large, accounting for nearly 80 percent of total energy production. This would limit the effect of the price of substitute in the coal industry demand.

A preliminary analysis of the aggregate coal series reveals that the demand has not always followed a regular trend, and in particular significant breaks occurred in different points in time. In fact, while the industrial coal demand grew steadily between 1990 and 1996, it declined in the period 1997-2000 and after this point it displayed a new rising trend. This suggests that the demand did not grow predictably with industrial production. In order to fully capture the evolution of the coal demand, an additive time trend is introduced as well as an interaction between the trend and the gross value added variable. We believe that this specification can proficiently capture potential structural changes occurring as a consequence of the rapid economic transformation. To account for the heterogeneity across provinces, fixed effects provincial dummies are added. Finally the variable population (POP) is included to control for provincial size differences.

To estimate the fixed effects spatial lag model and the fixed effects spatial error model[5], the three alternative spatial weight matrixes, described in Section 5 are used. It should be noted that the structure of the spatial dependence is maintained invariant with respect to time. Therefore, for estimation purposes, the weight matrix becomes:

$$\Psi = I_T \otimes W \tag{9}$$

where I_T is the T by T identity matrix, W is one of the N by N standardized weight matrix and $\otimes$ is the Kronecker product. This is because the way dependence is modeled here depends on geographical location, which does not vary over time. In matrix W3, on the contrary the structure depends not only on location but also on coal mines dimension. However, given the abundance of coal in China, it is plausible that the supply of fuel by the major coal mines did not experience significant drops over time.

Table 6 reports the estimated parameters. The estimates have the expected signs: the province size, expressed by the population variable, exerts a positive and highly significant impact on fuel demand. The coefficient of the variable RGVA alone is not statistically significant, whereas the interaction between the trend and variable RGVA exerts a positive and significant impact on coal.[6] This indicates that the marginal effect of output is not constant along the time. It should be noted that in the spatial lag model, the marginal effect of RGVA is given by the product of two terms, which are the estimated coefficient β and the spatial term $(I - \rho W)^{-1}$, as indicated by the reduced

[5] Anselin (2003), however, notes that the fixed effects model, which incorporates spatial dependence, is affected by incidental parameter problem.

[6] The possibile endogeneity of the output variable is tested in a non-spatial context, using the Wu-Hausman test. A one year lag of the RGVA variable is used as an instrument: this variable has the advantage of being highly correlated with the potential endogenous variable and orthogonal to the error process in the structural equation. The test cannot reject the hypothesis of exogeneity.

form in equation (4). [7] The computed elasticities of RGVA on coal have a positive value only in year 2002 and are reported in Table 7.

TABLE 6 HERE

The time trend has not an independent effect on coal demand. This may suggest that in the period considered no relevant technological improvement occurred in China.

The autocorrelation parameters are positive and always highly significant. With respect to the lag model, this indicates that the provincial industrial coal demand is influenced not only by standard economic factors, such as production and province size, but also by the existence of synergies among provinces in the energy production.

Given that transportation costs are likely to represent a significant component of final price, in particular under a regulated price system, it may be the case that the spatially lagged dependent variable captures part of this price effect. In fact, provinces located at close proximity with coal mines, clearly bear lower transportation costs, and this induces, *ceteris paribus*, a higher demand for coal. Therefore, it can also be the case that the inclusion of the spatially lagged variable partly compensates for the absence of the input prices.

Finally, the F-test on the fixed effect rejects the hypothesis that the provincial dummy coefficients are jointly zero.

Different tests have been developed to detect a model misspecification due to the existence of spatial dependence, in the form of spatially lagged dependent variable or spatial error autocorrelation. The Moran's *I* test conducted on the regression residuals is labeled unidirectional test, in the sense that under the alternative hypothesis, any form of spatial autocorrelation among the residuals is implied, as the test does not point a specific alternative. Tables 8 presents the results of the diagnostic test: a clear rejection of a standard model, which does not incorporate spatial dependence is indicated. In fact, regardless the weight matrix used, the Moran's *I* test suggests the existence of spatial dependence, notwithstanding it cannot favor a specific spatial process model. To speculate further the form of spatial correlation, Lagrange Multiplier (LM) test can be performed: in its plane form, it is a test against a single form of spatial correlation, either spatial lag or spatial error, as it assumes that the alternative spatial dependence is not present. For example, LM-lag is a test on $\rho = 0$ assuming that $\lambda = 0$. The limitation of this test is that it is not robust to

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[7] Given that the spatial weight matrixes are row-standardized, the product $(I - \rho W)^{-1} * i * \beta_{rgva}$, where i is a vector of ones, gives a constant vector. However in both matrix W2 and W3, the rows relative to some provinces contain only zero terms. Applying these matrixes, the above product returns a vector which contains two distinct values.

misspecification of the assumptions: in the previous example, for instance, the test is not valid if $\lambda \neq 0$. According to the Table reported, the LM tests reject the hypothesis of no spatial correlations in the residuals. However, given that both LM-lag and LM-error reject the null hypothesis, a misspecification of the assumption is likely to arise, invalidating the conclusion of the tests.

TABLE 7 HERE

To overcome the previous limitation and following the classical specification search approach (Florax et al., 2003), when both LM-lag and LM-err are significant, robust LM test should be employed. In fact, this robust test has the advantage of being robust to local misspecification. For example, the LM-lag in its robust version, tests that $\rho = 0$ in the presence of local misspecification in terms of spatial dependent error process. The interesting feature is that only through using the coal mine weight matrix, namely matrix W3, provincial autocorrelation is fully captured. In fact, while using matrix W2 both robust tests are inconclusive, applying matrix W3 the tests clearly favour the spatial lag model. This finding on the one hand provides support to the use of the W3 weight matrix, which takes into account the spatial structure of the coal mine zone, while on the other it explicitly discriminates against the spatial error specification. Finally the log-likelihood of the estimations points in a similar direction, as far as the spatial lag model, which uses the spatial weight matrix W3, shows the best fit.

TABLE 8 HERE

7. Forecasting

A further objective of this paper is to provide an accurate forecasting for the industrial coal demand in China at provincial level. We believe that both the use of a disaggregated background, which fully captures the heterogeneity between provinces, as well as the inclusion of a spatial structure, will improve the predictions. Baltagi and Li (2004) derive the best linear unbiased predictor (BLUP) for the *i*th location at a future period $T+S$ in the context of spatial autocorrelation.[8] The BLUP for the fixed effects spatial error model is computed as:

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[8] The authors provide derivation only in the context of the autoregressive error dependence model

$$\hat{C}_{i,T+S} = Z'_{i,T+S}\hat{\beta} + \hat{\mu}_i \tag{10}$$

where $\hat{\mu}_i = \overline{C}_{i.} - \overline{Z}'_{i.}\hat{\beta}$, $\overline{C}_{i.} = \sum_{t=1}^{T} C_{it} / T$ and $\overline{Z}_{i.} = \sum_{t=1}^{T} Z_{it} / T$.

This looks exactly like the BLUP for fixed effects without spatial correlation except that the parameters are estimated by MLE, assuming $\lambda \neq 0$.

The BLUP for the fixed effects spatial lag model is calculated as:

$$\hat{C}_{i,T+S} = \hat{\rho} W\hat{C}_{i,T+S} + Z'_{i,T+S}\hat{\beta} + \hat{\mu}_i \tag{11}$$

where $\hat{\mu}_i$ is defined as before and the parameters are estimated by MLE, assuming $\rho \neq 0$.[9]

To perform out-of-sample forecast till 2010, the exogenous drivers need to be computed at provincial level for the eight years ahead: the drivers are the industrial value added and population. Different alternative methodologies are applied to provide the better match between the actual computation and the information available from published economic outlook (IMF, 2006; ADB, 2007; UN, 2006). In particular, the provincial level forecasts of the covariates are first aggregated and then compared with the available country level information. An autoregressive and a time trend approach as well as four exponential smoothing methods are computed: among these are single smoothing, double smoothing, Holt-Winters with additive variation and Holt-Winters without seasonal component. Finally, for the industrial value added a fixed growth rate is applied.

In the period between 2002 and 2007 the WDI (2006) and IFS (2007) report an average annual income growth of 10 percent. At the same time, the economic outlooks predict that a prodigious income growth will continue in the country: in fact, growth in China is pushed by increases in total factor productivity and capital accumulation, and these factors guarantee a sustainable growth over the long term. Moreover, the high productivity growth rates are maintained by further improvements in politics and in the institutional framework. It should be noted that China adopts the so called Five-Year-Plan, which provides the guide rules for its economic development and guarantees a form of control upon the economic situation. The main target for the ongoing 11th Five-Year-Plan is a sustained growth rate of the national economy. For overall China, an economic growth around nine per cent is predicted between 2007 and 2010.

Among the six methodologies described, the forecast based on autoregressive series is the one that

[9] In the Appendix a detailed derivation of the formula for the FE model with spatially lagged dependent variable is provided.

performs better, as far as, aggregating the data from provincial to country level, it produces a measure of the industrial output in line with the expected growth indicator. A second check conducted on the computed prediction pertains the size of the provincial shares to total country output. The contributions of the single provinces remained almost constant between 1995 and 2002 and no variation in this structure is expected to arise for the future periods. Moreover Aziz and Duenwald (2001), for example, report large performance discrepancies among provinces and uneven regional development. However, they also state that, despite the consideration of the growth literature, the convergence in income within China it is not likely to happen in the coming future. Therefore the preferred methodologies are those which maintain a stable provincial share over the considered horizon: these are the autoregressive series, the Holt-Winters without seasonal variation, and the double smoothing.

Similar considerations are adopted to identify the preferred population series to apply in the forecasting. UN (2006) provides the baseline indicator for the population trend at country level: this data set predicts a steady population growth at around one per cent for China. Moreover, the 11th Five-Year-Plan clearly states that the rate of increase in China's population should be maintained within one percent. Both the time trend approach and the double smoothing are in line with this prediction.

The selected series for population and gross value added are used to formulate forecast of the industrial coal demand. The estimated parameters from the previous econometric analysis are applied, assuming no structural change in the overall economic and technological context. We are aware this is a strong assumption, in particular as far as China is pursuing a target for ensuring an efficient, reliable but also environmentally tolerant power industry (IEA, 2006), which will require a set of reforms in the energy sector. It is also true, nevertheless, that the technological paradigm is likely to be maintained during the forecast period, as the time length considered for prediction is fairly short.

The forecast is performed applying the econometric models discussed above: the FE-model with spatial error and the FE-model with spatial lag dependence. To incorporate the spatial structure, only matrix W3 is considered, given that it seems to be the matrix which better captures the spatial autocorrelation. The outcome is reported in Table 9. Depending on the specification and on the models used, the predicted average annual increase in industrial coal demand varies between 2.5 and four percent. Nevertheless, if we consider the spatial lag model only, the estimated annual growth varies within 3.2 and four percent. In particular, specification A, which uses the AR method for RGVA and the double smoothing for population predicts growth rate of four percent, which is almost in line with the forecast suggested by the International Energy Agency, which indicates an average annual industrial coal increase of 4.5 percent over the period 2004-2015. A slightly lower forecast is produced by Crompton and Wu (2005), who report an annual growth rate of 3.3 per cent for coal, over the period 2001-2010. Finally Dong (2000), applying an uncertain dynamic system modelling approach, predicts over the period 2000-2010 an average annual increase of coal of five percent.

Figure 3 displays the ascending trend of the forecasts produced by the two models applying drivers specification A: as already discussed, the spatial lag model seems to better capture the growth scenario anticipated by the available energy outlooks.

Finally the industrial coal predictions for 2010, disaggregated by provinces, are reported in Table 10. The leading position of the provinces located at close distance from the coal mines seem to be maintained throughout the time. In fact, the ten major demanding provinces highlighted in the initial analysis[10] are those which are more likely to demand the higher level of coal in the future.

8. Conclusions

In recent years, concerns regarding the environmental implications of the rising energy demand, induces considerable efforts to generate long term forecasting of China's coal requirements. The economic analysis, which are all conducted at the country level, are almost unanimous in projecting increasing trend in coal demand. To our knowledge, however, no prior study models the coal demand in China at provincial level and produces future forecasting. The availability of a data set at provincial level allows us to fill in the current gap in research. In this paper we have analysed the Chinese industrial coal demand using a panel disaggregated by provinces. Moreover, given the nature of the data, the spatial autocorrelation between provinces has been captured, using a spatial econometric model.

The dependent variable of our model is the provincial level industrial coal demand, which includes industrial energy demand, industrial non energy demand and the consumption lost during the process of energy conversion. A preliminary analysis of the aggregate coal series has revealed that the demand has not always followed a regular trend, and in particular significant breaks occurred in different points in time. In fact, while the industrial coal demand grew steadily between 1990 and 1996, it declined in the period 1997-2000 and after this point it displayed a new rising trend. This behaviour suggests that the demand did not grow predictably with industrial production. In order to fully capture the evolution of the coal demand, an additive time trend has been introduced, as well as an interaction between the trend and the gross value added variable. To account for the

[10] See Table 2.

heterogeneity across provinces, fixed effects provincial dummies have been added. Finally, population is included to control for provincial size differences.

The estimates have shown the expected signs: the province size, expressed by the population variable, exerts a positive and highly significant impact on fuel demand. The coefficient of real gross value added alone is not statistically significant, whereas the interaction between the trend and real gross value added exerts a positive and significant impact on coal. This indicates that the marginal effect of output is not constant along the time. The time trend has not an independent effect on coal demand. This may suggest that in the period considered no relevant technological improvement occurred in China. The autocorrelation parameters are positive and always highly significant. With respect to the lag model, this indicates that the provincial industrial coal demand is influenced not only by standard economic factors, such as production and province size, but also by the existence of synergies among provinces in the energy production.

Different tests have been developed to detect a model misspecification due to the existence of spatial dependence, in the form of spatially lagged dependent variable or spatial error autocorrelation. A clear rejection of a standard model, which does not incorporate spatial dependence is indicated.

A further objective of this paper was to provide an accurate forecasting for the industrial coal demand in China at provincial level. We have shown that both the use of a disaggregated background, which fully captures the heterogeneity between provinces, as well as the inclusion of a spatial structure, improves the predictions. To perform out-of-sample forecast till 2010, the exogenous drivers need to be computed at provincial level for the eight years ahead, the drivers being the industrial value added and population. Different alternative methodologies have been applied to provide the better match between the actual computation and the information available from published economic outlooks. Among the alternative methodologies adopted, the forecast based on autoregressive series is the one that performs better, as far as, aggregating the data from provincial to country level, it produces a measure of the industrial output in line with the expected growth indicator. Similar considerations are adopted to identify the preferred population series to apply in the forecasting.

The forecast is performed applying the econometric models discussed above: the fixed effects model with spatial error and the fixed effects model with spatial lag dependence. Depending on the specification and on the models used, the predicted average annual increase in industrial coal demand varies between 2.5 and four percent. Nevertheless, if we consider the spatial lag model only, the estimated annual growth varies within 3.2 and four percent. Finally the industrial coal predictions for 2010, disaggregated by provinces, have been computed. The leading position of the provinces located at close distance from the coal mines seem to be maintained throughout the time. In fact, the ten major demanding provinces highlighted in the initial analysis are those which are more likely to demand the higher level of coal in the future.

Appendix

Consider the following spatial panel data model:

$$C_{it} = \rho W C_{it} + Z_{it}^{'}\beta + u_{it}$$

$$u_{it} = \mu_i + \varepsilon_{it}$$

for i=1,…, N; t=1,…, T. Rearranging the model we obtain:

$$C_{it} = B^{-1} Z_{it}^{'}\beta + B^{-1}\mu_i + B^{-1}\varepsilon_{it}$$

where $B = (I - \rho W)$. Goldberger (1962) demonstrates that the best linear unbiased predictor (BLUP) contains a correction term which depends upon the variance-covariance matrix of the error term (Ω) and upon the covariance matrix between future and current disturbances (ω). To obtain the BLUP of $C_{i,T+S}$ therefore, we need to compute $\Omega = E(\varepsilon\varepsilon')$ and $\omega = E(\varepsilon_{i,T+S}\varepsilon)$.
The variance-covariance matrix is given by:

$$\Omega = E(\varepsilon\varepsilon') = \sigma_{\varepsilon}^{2}(I_T \otimes (B'B)^{-1})$$

It should be noted that in a fixed effect model $\omega = E(\varepsilon_{i,T+S}\varepsilon) = 0$, since the ε are not serially correlated over time. Therefore, the correction term $\omega'\Omega^{-1}\varepsilon$ cancels out and the BLUP of $C_{i,T+S}$ becomes:

$$\hat{C}_{i,T+S} = \hat{B}^{-1} Z_{i,T+S}^{'}\hat{\beta} + \hat{B}^{-1}\hat{\mu}_i$$

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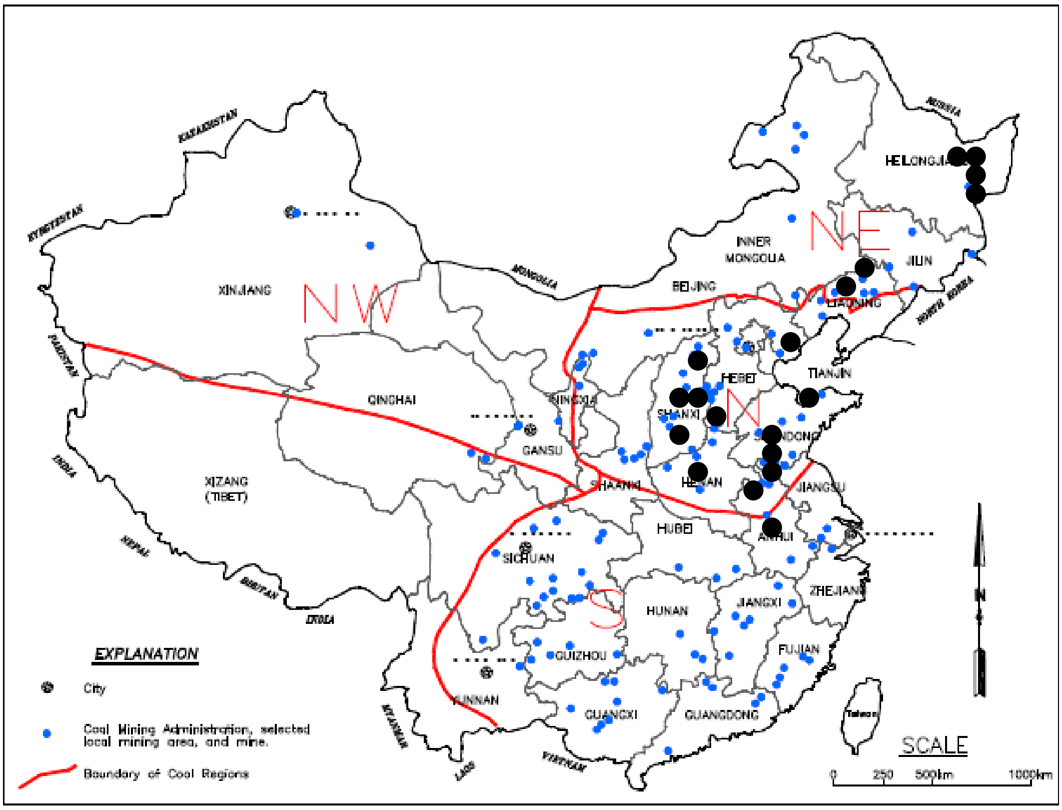
Figure 1. Location of the major coal mines (mines which produce more than 10 million tonnes)



Source. EPA, 1996

Figure 2. Industrial coal demand clusters: 8 years average (million tonnes, Mt)

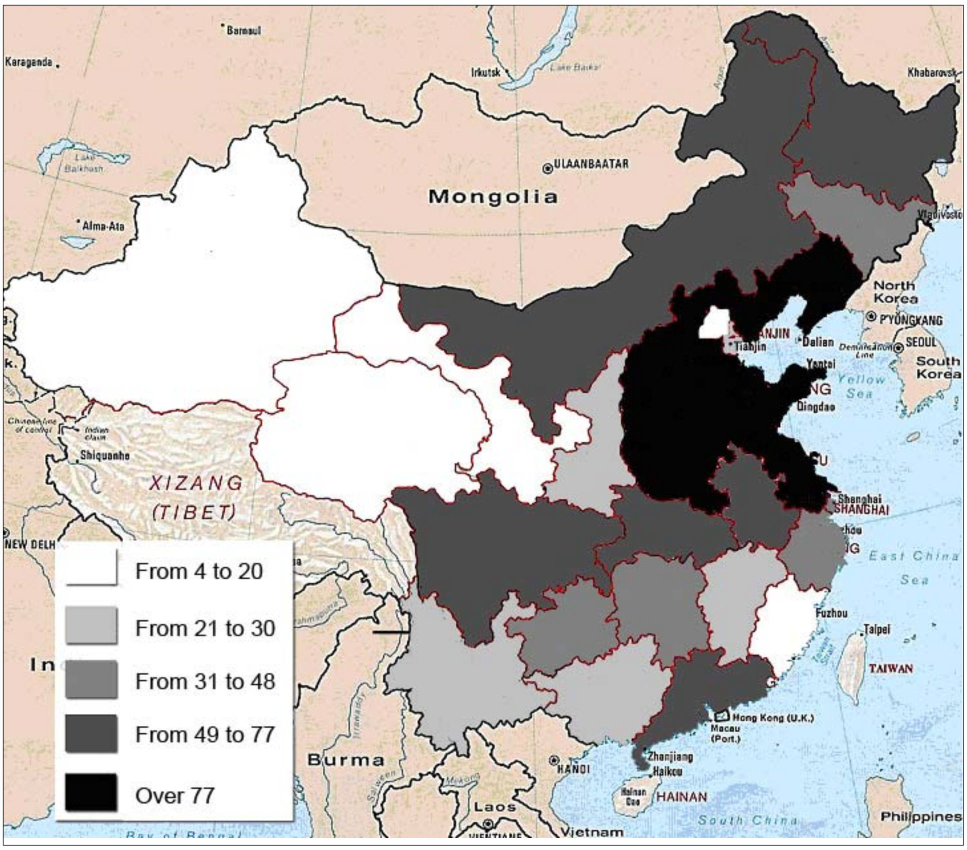


Table 1. Coal production for major coal mines

Coal mine	Province	Coal production (thousand tonnes per year)
Datong	Shanxi	31754.6
Kailuan	Hebei	17604.8
Pingdingshan	Henan	17147.8
Huaibei	Anhui	14232.1
Xishan	Shanxi	14127.7
Hegang	Heilongjiang	13130.7
Xuzhou	Jiangsu	13103.1
Fuxin	Liaoning	12698.7
Longkou	Shandong	12003.1
Yanzhuo	Shandong	12003.1
Jixi	Heilongjiang	11644.2
Huainan	Anhui	11498.5
Yangquan	Shanxi	10476.9
Fengfeng	Hebei	10370.0
Jincheng	Shanxi	10320.6
Tiefa	Liaoning	10241.0
Xinwen	Shandong	10089.0
Qitaihe	Heilongjiang	10060.1
Shuangyashan	Heilongjiang	10015.5

Source. EPA, 1996

Table 2. Industrial coal demand for selected provinces (million tonnes, Mt)

Province	1995	1996	1997	1998	1999	2000	2001	2002
Shanxi	140.0	143.8	137.7	143.5	128.4	133.2	138.8	170.1
Hebei	90.8	92.0	92.3	94.8	96.7	101.6	106.5	117.8
Shandong	86.6	91.6	91.5	87.1	86.1	75.3	94.7	110.9
Jiangsu	83.1	83.2	79.9	81.8	83.4	84.5	87.1	94.0
Henan	66.7	69.6	65.4	68.1	71.0	76.9	83.1	93.7
Liaoning	81.5	80.9	79.7	76.4	73.9	86.0	81.2	84.0
Guangdong	45.3	47.7	48.6	48.1	50.8	57.3	58.9	64.8
Inner Mongolia	37.7	40.6	48.6	44.1	48.3	53.4	57.1	63.4
Anhui	44.8	47.5	49.0	48.0	50.0	53.2	57.2	59.7
Zhejiang	39.5	43.2	45.1	44.3	45.8	48.3	53.5	58.6

Source. Authors' computation from China Energy Databook (2004)

Table 3. Global Moran statistic on average industrial coal

Moran's I	I	E(I)	sd(I)	z	P-value
W1	0.305	-0.038	0.122	2.811	0.005
W2	0.321	-0.038	0.156	2.303	0.021
W3	1.113	-0.038	0.206	5.588	0.000

Notes. The P-value refers to a two-tail test of no spatial autocorrelation, which corresponds to z=0

Table 4. Global Geary statistic on average industrial coal

Geary's *c*	*c*	E(*c*)	sd(*c*)	z	P-value
W1	0.624	1.000	0.141	-2.665	0.008
W2	0.728	1	0.185	-1.469	0.142
W3	0.587	1.000	0.463	-0.894	0.371

Notes. The P-value refers to a two-tail test of no spatial autocorrelation, which corresponds to z=1

Table 5. Local Moran statistic on average industrial coal for selected provinces

Province	I_i	P-value	I_i	P-value	I_i	P-value
	W1		W2		W3	
Beijing	-0.37	0.61	0.10	0.84	0.74	0.23
Tianjin	-0.35	0.63	0.07	0.86	0.73	0.24
Hebei	1.17	0.00	1.84	0.00	2.42	0.00
Shanxi	1.59	0.00	2.42	0.00	4.43	0.00
Inner Mongolia	0.04	0.80	0.10	0.78	0.10	0.79
Shaanxi	-0.33	0.40	-0.64	0.25	-	-
Gansu	0.51	0.16	1.04	0.14	-	-
Qinghai	0.84	0.09	1.29	0.16	-	-
Xinjiang	1.18	0.06	-	-	-	-
Liaoning	0.54	0.27	-0.15	0.88	0.45	0.46
Jilin	-0.13	0.87	-0.16	0.86	-0.11	0.91
Heilongjiang	-0.03	0.99	-0.01	0.97	-	-
Shanghai	-0.14	0.88	-0.05	0.99	-	-
Jiangsu	0.40	0.32	0.10	0.77	0.88	0.04
Zhejiang	0.00	0.92	0.00	0.94	-	-
Anhui	0.06	0.77	0.08	0.80	0.09	0.77
Fujian	0.19	0.66	0.33	0.49	-	-
Jiangxi	0.12	0.66	0.00	0.92	-	-
Shandong	1.39	0.00	0.62	0.07	1.99	0.00
Henan	0.87	0.01	0.91	0.00	1.57	0.00
Hubei	-0.01	0.94	-0.01	0.95	0.06	0.85
Hunan	0.10	0.69	0.07	0.83	-	-
Guangdong	-0.13	0.83	-0.11	0.91	-	-
Guangxi	0.30	0.45	0.17	0.75	-	-
Sichuan	-0.09	0.88	-0.10	0.91	-	-
Guizhou	0.21	0.57	0.26	0.57	-	-
Yunnan	0.30	0.52	0.19	0.73	-	-

Notes. The P-value refers to a two-tail test of no spatial autocorrelation. For some provinces the local statistic is not computed as it results no neighbour associated to these locations, according to the criteria applied.

Table 6. Fixed effect estimates of industrial coal demand

	W1		W2		W3	
	Error model	Lag model	Error model	Lag model	Error model	Lag model
RGVA	-0.018	-0.018	-0.016	-0.017	-0.017	-0.016
	(0.016)	(0.014)	(0.017)	(0.014)	(0.015)	(0.013)
lnTrend*RGVA	0.026	0.025	0.025	0.025	0.022	0.02
	(0.009)***	(0.008)***	(0.009)***	(0.008)***	(0.008)***	(0.007)***
lnTrend	1.303	0.28	1.347	-0.069	0.125	0.049
	(1.836)	(1.475)	(1.840)	(1.342)	(1.138)	(1.018)
POP	0.958	0.972	1.001	0.999	0.944	0.947
	(0.074)***	(0.072)***	(0.073)***	(0.074)***	(0.074)***	(0.073)***
Constant	8.926	-2.607	8.135	-1.876	9.437	-0.876
	(1.845)***	(5.965)	(1.896)***	(4.802)	(1.757)***	(2.458)
Observations	216	216	216	216	216	216
Log-likelihood	-605.005	-604.317	-600.940	-601.521	-592.59897	-584.833
λ	0.199		0.270		0.5283	
	(0.118)*		(0.099)***		(0.111)***	
ρ		0.193		0.239		0.4878
		(0.096)**		(0.096)**		(0.088)***
Joint test for provincial dummies	5438.55 P=0.000	6156.88 P=0.000	6690.27 P=0.000	7671.27 P=0.000	6181.19 P=0.000	6482.12 P=0.000

Notes. Maximum likelihood estimation is used. Robust standard errors in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%. The ln(Trend) variable takes the value of zero between 1995 and 2000. It values 0.69 in 2001 and 1.10 in 2002. The spatial weights matrix W1 is computed setting $\omega_{ij} = 1$ if province *i* and *j* share common borders and 0 otherwise, and then computing a row standardization. The spatial weights matrix W2 is computed setting $\omega_{ij} = 1/Dist_{ij}^2$, where $Dist_{ij}$ is the Euclidean distance between province *i* and *j*, if $Dist_{ij}$ is less than or equal to 600 Km and 0 otherwise, and then applying a row standardization. The weights matrix W3 is computed setting $\omega_{ij} = 1$ if in the common neighbourhood of provinces *i* and *j*, it exists at least one major mine and 0 otherwise and then applying a row standardization. Major mine is defined here as producing more than 10 million tonnes of coal and the common neighbourhood is defined in the circle area of 300 km from the capital of the province. The test on the province dummies is distributed as a χ^2 (26).

Table 7. The elasticity of RGVA on coal: year 2002

		W1		W2		W3	
Region	Province	Error	Lag	Error	Lag	Error	Lag
North	Beijing	0.08	0.08	0.08	0.1	0.05	0.08
	Tianjin	0.04	0.04	0.04	0.05	0.03	0.04
	Hebei	0.03	0.03	0.03	0.03	0.02	0.03
	Shanxi	0.01	0.01	0.01	0.01	0.004	0.01
	Inner Mongolia	0.01	0.01	0.01	0.02	0.01	0.01
	Mean	0.03	0.03	0.03	0.04	0.02	0.03
	st.dev	0.03	0.03	0.03	0.04	0.02	0.03
Northeast	Liaoning	0.03	0.04	0.03	0.04	0.02	0.04
	Jilin	0.03	0.03	0.03	0.04	0.02	0.03
	Heilongjiang	0.04	0.04	0.04	0.05	0.02	0.02
	Mean	0.03	0.04	0.03	0.04	0.02	0.03
	st.dev	0.01	0.01	0.01	0.01	0.00	0.01
East	Shanghai	0.06	0.07	0.06	0.08	0.04	0.03
	Jiangsu	0.06	0.06	0.06	0.07	0.04	0.06
	Zhejiang	0.07	0.07	0.07	0.08	0.04	0.04
	Anhui	0.03	0.03	0.03	0.04	0.02	0.03
	Fujian	0.09	0.1	0.1	0.12	0.06	0.05
	Jiangxi	0.05	0.06	0.06	0.07	0.04	0.03
	Shandong	0.05	0.05	0.05	0.06	0.03	0.05
	Mean	0.06	0.06	0.06	0.07	0.04	0.04
	st.dev	0.02	0.02	0.02	0.02	0.01	0.01
South-Central	Henan	0.03	0.04	0.04	0.04	0.02	0.04
	Hubei	0.04	0.05	0.05	0.06	0.03	0.05
	Hunan	0.06	0.06	0.06	0.07	0.04	0.03
	Guangdong	0.09	0.1	0.1	0.12	0.06	0.05
	Guangxi	0.06	0.06	0.06	0.08	0.04	0.03
	Mean	0.06	0.06	0.06	0.07	0.04	0.04
	st.dev	0.02	0.02	0.02	0.03	0.01	0.01
Southwest	Sichuan	0.05	0.06	0.05	0.07	0.03	0.03
	Guizhou	0.02	0.02	0.02	0.02	0.01	0.01
	Yunnan	0.04	0.04	0.04	0.05	0.03	0.02
	Mean	0.04	0.04	0.04	0.05	0.02	0.02
	st.dev	0.02	0.02	0.02	0.03	0.01	0.01
Northwest	Shaanxi	0.03	0.04	0.03	0.04	0.02	0.02
	Gansu	0.03	0.03	0.03	0.03	0.02	0.01
	Qinghai	0.03	0.04	0.04	0.04	0.02	0.02
	Xinjiang	0.04	0.04	0.04	0.04	0.03	0.02
	Mean	0.03	0.04	0.04	0.04	0.02	0.02
	st.dev	0.005	0.005	0.006	0.005	0.005	0.005
Overall	Mean	0.04	0.05	0.05	0.06	0.03	0.03
	st.dev	0.02	0.02	0.02	0.03	0.01	0.02

Table 8. Spatial tests

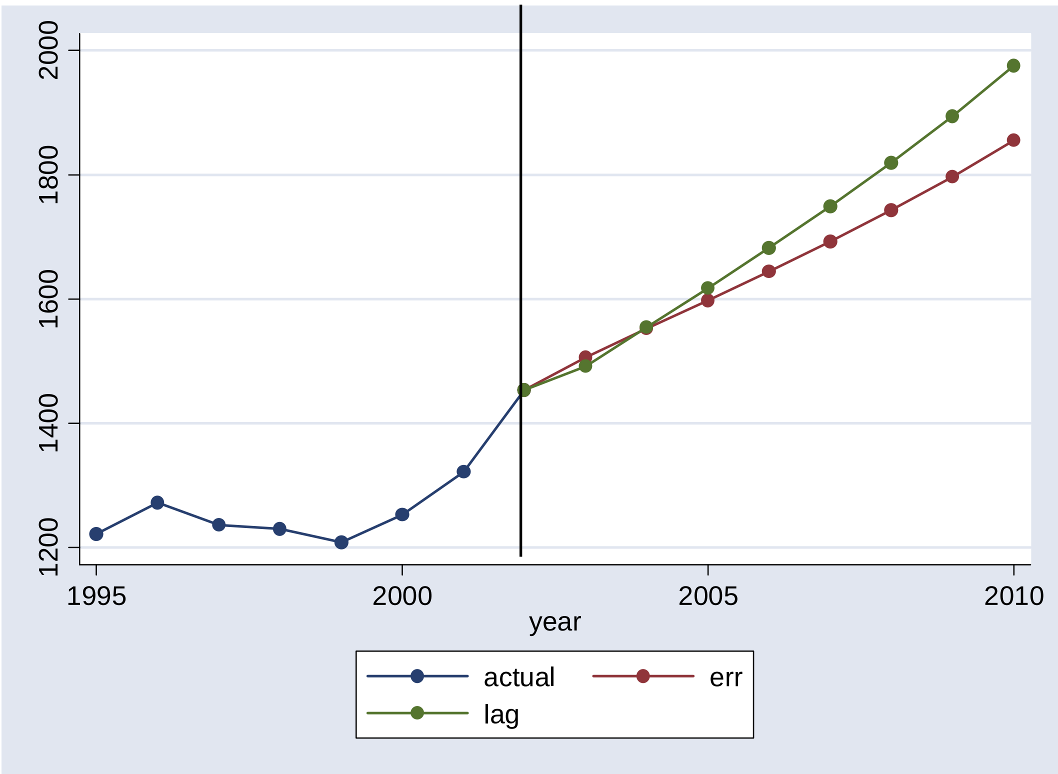
Test	Statistic	P-value	Statistic	P-value	Statistic	P-value
	W1		W2		W3	
Moran's *I*	2.382	0.017	3.735	0.000	20.751	0.000
Spatial error: LM-err	5.145	0.023	13.278	0.000	87.422	0.000
Robust Lagrange multiplier	0.009	0.926	1.193	0.275	0.498	0.481
Spatial lag: LM-lag	6.663	0.010	12.194	0.000	120.441	0.000
Robust Lagrange multiplier	1.527	0.217	0.109	0.741	33.517	0.000

Table 9. Industrial coal demand forecasts: years 2005, 2010 (Mt)

Drivers specification	Model	Aggregate industrial coal demand		
		Prediction 2005	Prediction 2010	Average annual percent change 2002-2010
A	err	1598	1855	3.06
	lag	1618	1975	3.98
B	err	1585	1831	2.88
	lag	1605	1952	3.80
C	err	1581	1776	2.46
	lag	1599	1875	3.21
D	err	1593	1800	2.64
	lag	1611	1898	3.39
E	err	1580	1776	2.46
	lag	1598	1874	3.21
F	err	1593	1799	2.63
	lag	1611	1897	3.38

Notes. The AR method for RGVA is applied in the drivers specifications A and B. The Holt-Winters for RGVA is used in drivers specifications C and D whereas the double-smoothing is used in drivers specifications E and F. For population, specifications A, D and F use double-smoothing, while specifications B, C and E apply trend. The measures refer to total China industrial coal demand despite being not exhaustive: in fact, only the 27 provinces- on a total of 30- considered in the analysis contributed to the aggregation. The percentage change is computed with reference to year 2002, where the actual industrial coal is 1454.

Figure 3. Industrial coal demand forecasts: years 2003-2010 (Mt)



Notes. The graph refers to the scenario suggested by drivers specification A.

Table 10. Industrial coal demand forecasts by provinces: years 2005, 2010 (Mt)

Region	Province	Prediction 2005	Prediction 2010
North	Beijing	33.73	52.90
	Tianjin	30.68	43.16
	Hebei	121.16	141.81
	Shanxi	157.24	171.95
	Inner Mongolia	60.20	71.30
Northeast	Liaoning	96.96	113.04
	Jilin	50.50	62.53
	Heilongjiang	62.39	68.47
East	Shanghai	50.25	59.27
	Jiangsu	117.21	156.36
	Zhejiang	63.54	91.44
	Anhui	72.88	92.57
	Fujian	27.29	34.74
	Jiangxi	27.58	30.81
	Shandong	122.42	157.68
South-Central	Henan	99.71	122.89
	Hubei	71.78	90.03
	Hunan	44.70	51.27
	Guangdong	78.17	103.21
	Guangxi	28.18	34.85
Southwest	Sichuan	50.44	53.30
	Guizhou	38.00	42.40
	Yunnan	30.42	34.51
Northwest	Shaanxi	33.88	38.86
	Gansu	22.17	24.02
	Qinghai	5.16	6.80
	Xinjiang	21.04	25.22

Notes. The reported provincial predictions refer to driver specification A and spatial lag model.

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