THE COST OF ENERGY – THE ENVIRONMENTAL EFFECTS OF COAL PRODUCTION IN CHINA

Nyakundi Michieka, Graduate Research Assistant, Environmental and Natural Resource Economics, West Virginia University

Phone: +1 304-293-5403

Email: nyakundi.michieka@mail.wvu.edu

Jerald Fletcher, Professor, Energy, Environmental and Natural Resource Economics, West Virginia University

Phone: +1 304-293-5499

E-mail: jerry.fletcher@mail.wvu.edu

Wesley Burnett, Research Assistant Professor, Division of Resource Management, West Virginia University

Phone +1 304-293-5639

E-mail: wesley.burnett@mail.wvu.edu

1 INTRODUCTION

The immense economic growth of the Chinese economy has been accompanied by an increase in energy demand, greater coal combustion, and larger pollution emissions. China leads the world in the production and consumption of coal (World Coal Association 2012). Coal is the country's primary energy source as shown in Figure 1 (US Energy and Information Administration 2010). China uses more coal than the United States, Europe and Japan combined (Moore 2011; Vince 2012). Its environmental problems are among the most severe of any major country and are mostly getting worse (Liu and Diamond 2005).

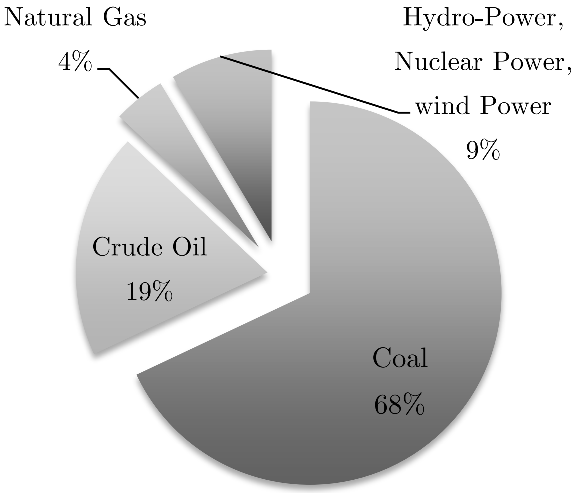

Figure 1: China's Consumption of Energy (2010)
Source: China Statistical Yearbook

This paper seeks to analyze the relationship between the environment and coal production. Coal, which is the primary energy source in China is the dirtiest of fuels (Parker 2004). The process of mining, cleaning, transporting coal to electricity generation and disposal leaves pollutants in the air water and lands (Cantú 2005). The accumulative impacts affect the health of China's citizens and place costs to the government. There are calls by the Chinese government and environmental organizations to improve the environment, prompting the need to investigate the coal production-environment nexus.

The main objective of this paper is to conduct a spatial analysis of how the environment and various factors affect coal production in China. Findings from this study will contribute to an understanding of the literature on the association between coal production and the environment. This study is unique in the sense that it analyzes this nexus within a spatial econometric framework. Results from the analysis will assist to draw appropriate policy implications for improving coal production in China.

The reminder of the paper is organized as follows: The next section describes some of the effects of coal production on the environment while section 3 describes the model used for the analysis. Section 4 presents the empirical results while the final section concludes the paper.

2 COAL AND THE ENVIRONMENT

Coal Production

In 2009, China produced 3.4 billion tons of coal making it the largest coal producer in the world (Meng, Feng et al. 2009). America, India and Australia also produced large amounts of coal as illustrated in Figure 2. Most of China's coal is produced in 27 provinces, with Shanxi and other northern provinces producing the largest quantities as shown in Figure 3. 95 percent of the coal mined is from underground mines which have a productive life of half century (Meng, Feng et al. 2009). Coal is produced from large modern state mines or local state mines which are smaller and partially mechanized. Coal is also produced from township and village enterprise mines which are small, use manual extraction techniques which are dangerous, and waste resources (Minchener 2005).

The environmental effects of mining coal depend on whether the mine is active or abandoned, the mining methods used in addition to the sites' geological conditions (Bell, Bullock et al. 2001). They include ground subsidence, hydrodynamics change, land use change, soil pollution, and ecosystem evolution. Coal mining is a water intensive process which leads to reduced ground water levels in some areas. Long time dumping of coal gangue causes accumulation hazardous substances which leach into the soil resulting in soil pollution. According to the Chinese government, costs of environmental damage from coal mining total RMB 30 billion per year (International Energy Agency 2009). Coal use contributes to global atmospheric problems (Meng, Feng et al. 2009). Electricity production contributes to SO2 emissions which lead to the formation of acid rain which cause crop loss and forest decline (Larssen, Seip et al. 1999). China is the largest contributor of carbon dioxide emissions in the world (Netherlands Environmental Assessment Agency 2007; Su, Li et al. 2011). Its dust and aerial pollutants are transported eastwards to neighboring countries including North America.

Coal is first mined and processed before it is burned to generate power. This process generates spillover effects especially in areas with large reserves where mining is active (Bian, Inyang et al. 2010). Vast swathes of coal in northern China have been mined, leaving millions of people living precariously on the land above (Moore 2011; Vince 2012). Residents in China's coal belt continue to live in choking clouds of soot and roaring mines as they face the threat of being buried alive. In Shanxi, the threat of being buried was so high that residents had to migrate. In Pangpangta, residents witnessed the collapse of more than 200 houses (Moore 2011).

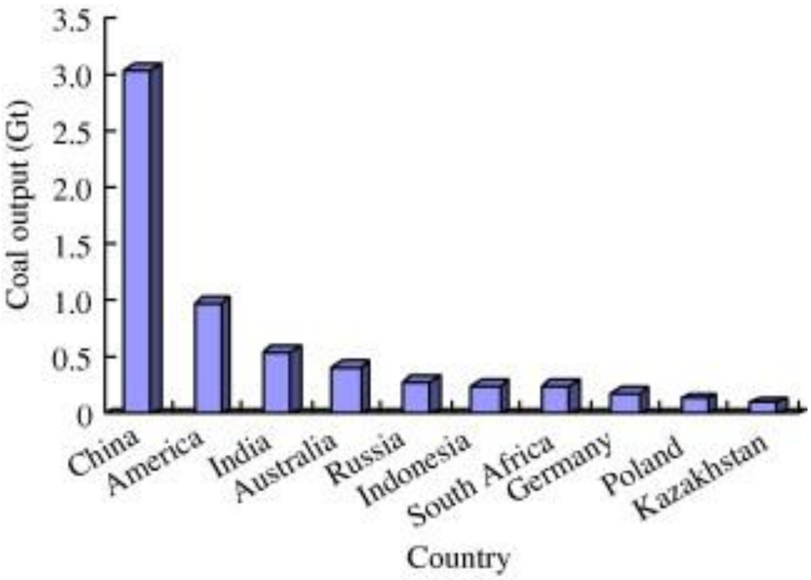

Figure 2: National Coal Output of Global Top 10 Countries in 2009

Source: (Wu, Jiang et al. 2011)

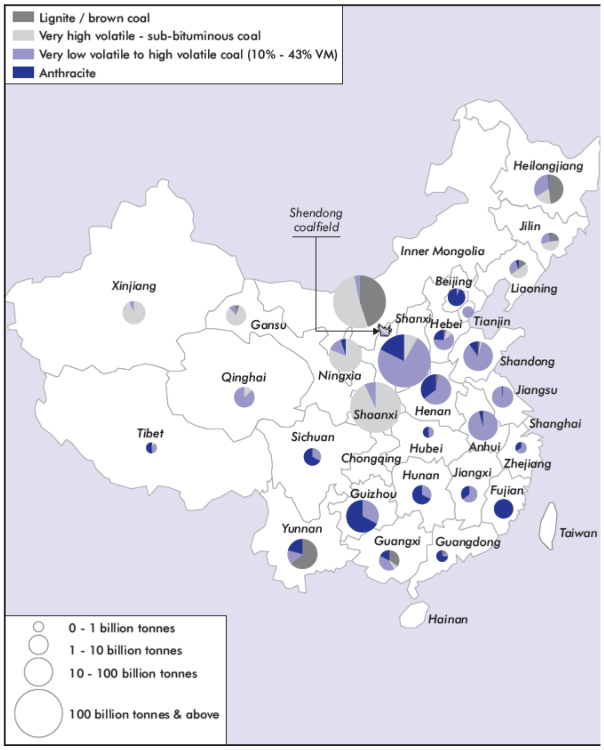

Figure 3: China's Mainland Coal Resources

Source: (International Energy Agency 2009)

Although China possesses world's second largest proven coal reserves after the United States, it has been involved in exporting and importing coal. Figure 4 describes coal import – export pattern from 1980-2009. China mainly imports coal from Indonesia, Australia, Vietnam and Russia (US Energy and

Information Administration 2010). Its imports grew after 2002 because costs of importing coal became competitive with domestic production. In 2009, China became a net importer after historically being a net exporter. As of April 2012, China's coal imports were double those of April 2011. This rise is attributed to increasing electricity demand and lower international coal prices (Zhu and Sethuraman 2012).

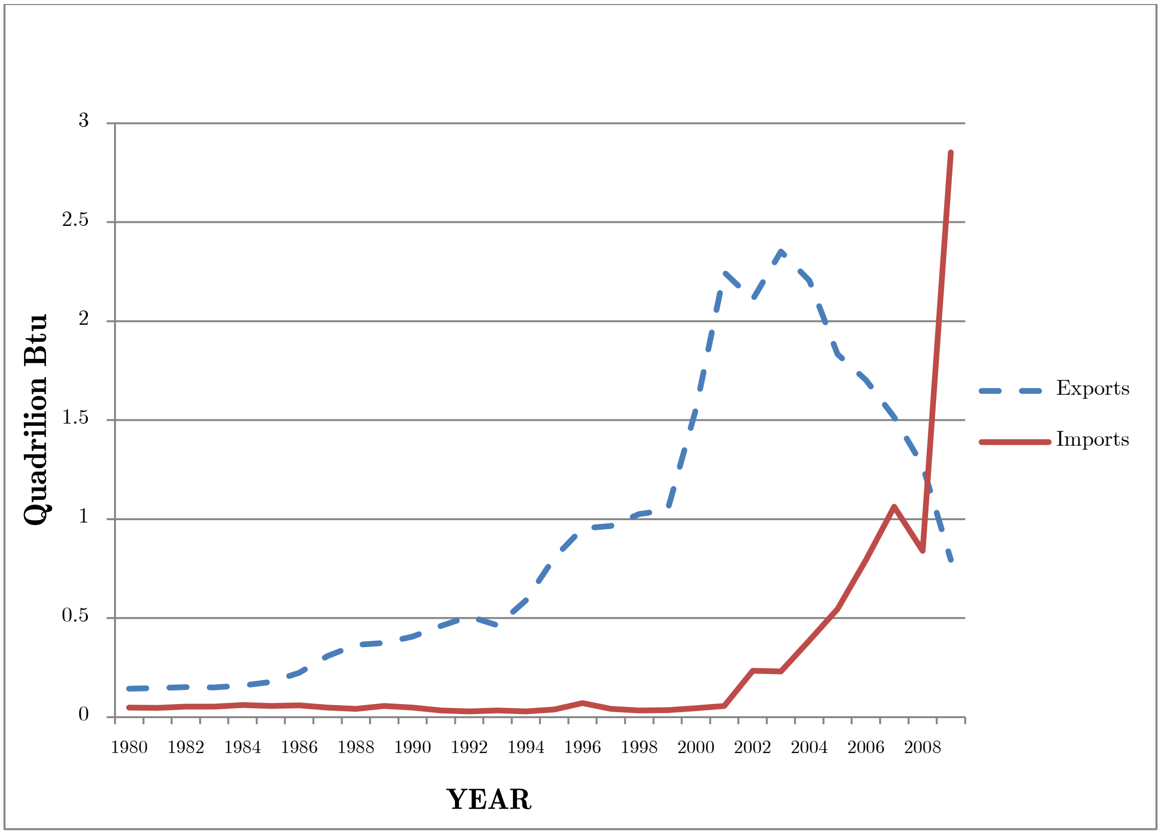

Figure 4: Coal Exports and Imports in China (1980-2009)

Source: Adapted from the Energy and Information Administration (EIA)

The coal energy production system consists of mining, preparation and energy generation. A process which produces waste at different stages. Identifying the wastes at each process is a step towards reducing the adverse environmental effects of mining, and one that will make the industry a more sustainable one. Figure 5 shows the process of producing energy from coal. In this study, the adverse environmental effects of coal production will be analyzed. A focus will be placed on the mining, preparation and energy generation stages. Emphasis will be placed on the prior two sections.

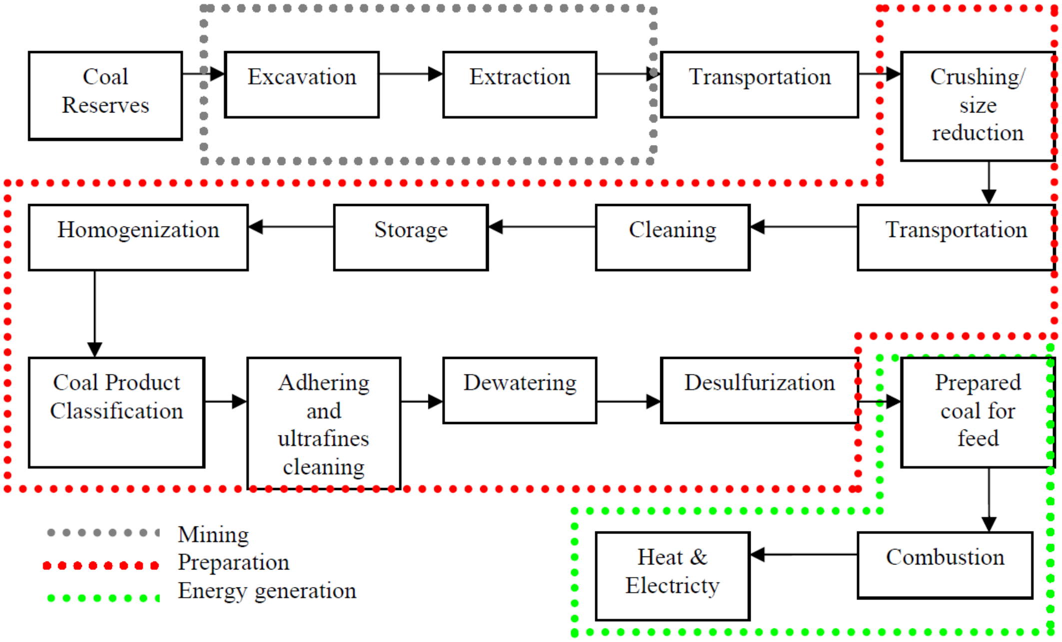

Figure 5: Coal Energy System

Source: (Cantú 2005)

As pointed out in the Introduction, there are four aspects of the coal production-environment problem, namely (1) Water pollution, (2) Air pollution, (3) Waste, and (4) Land subsidence. We also revisit the issue of deaths and transportation in this study.

2.1 Water Pollution

China is endowed with rich water resources but is relatively poor in terms of water resources per capita (Hubacek, Guan et al. 2009). Reports indicate that China's demand for coal is outpacing its freshwater supply. Coal is the largest consumer of fresh water which it uses for extraction and processing. However, water resources are abundant in the south and east but insufficient in the north and west where they are needed most for mining activities. Interestingly, the spatial distribution of China's coal resources is the reverse (Sun, Wu et al. 2012). Lately, the urbanization boom has caused a surge in demand for energy and water. The relationship between coal mining and water use varies with location and activity. Coal mining affects the water environment by causing a drop in the ground water table. Mining activities also pollute the water in addition to altering the direction of water courses. In eastern China where most mining is underground, continued mining in the lower seams has increased the risk of high-pressure karst water bursting into the mine. The central and Xinjiang coal regions have thick coal seams located relatively near the surface. Large-scale mechanized coal mining in these areas disturbs overburden strata that bears surface water while threatening the safety and production of mining activities. To note, eleven of the fourteen large coal producing regions are located in arid and semi-arid areas where water is in short supply (Sun, Wu et al. 2012).

2.2 Air Pollution

Mining activities cause emissions of sulfur dioxide, methane, and oxides of nitrogen, which are major contributors of global warming (Bian, Inyang et al. 2010). Surface mining operations involve drilling, blasting, and movement of heavy earth machinery which lead to acid mine drainage (AMD). AMD occurs when coal beds and surrounding strata are disrupted by mining activities, exposing sulfides to air and water. Burning of medium to high-sulfur coal leads to the formation of sulfur oxides (SO2) and acid rain (Schweinfurth 2005). Presently, China is the largest emitter of SO2 in the world owing to increased coal use. Acid rain from SO2 emissions has caused damages to crops amounting to 30 billion Yuan, which, according to the World Bank, is equivalent to 1.8 percent the value of agricultural output (The World Bank 2007). Methane, the main component of coal gas, is a major contributor of the greenhouse effect. Spontaneous combustion of coal gangue also contributes to the cumulative effect of air pollution. These activities have caused annual methane emission in China to reach 7.0~9.0 billion cubic meters.

2.3 Waste

Mining produces large quantities of waste which include gangue, sludge, fly-ash, coal mine drainage and coal-bed methane. Improperly piled gangue can cause landslides, spontaneous combustion of harmful gases, acid rain formation and toxic substances (Haibin and Zhenling 2010). Waste from underground mining comprise of coarse discard which is produced by the washing process. They cause erosion, dust pollution driven by wind, air pollution, spontaneous combustion, visual and landscape impacts and land use constraints. The impact of mining waste can have lasting environmental and socio-economic consequences and be extremely difficult and costly to address (Bell, Bullock et al. 2001). Various studies have proposed different ways of putting this waste to good use. Bian et al., (2009) proposed that filling mining wastes into a subsidence basin could reclaim that land which could be used for agricultural purposes. They also suggested that the waste be used to make bricks, fuel power plants or fill underground cavities left by mining.

2.4 Land subsidence

Land subsidence is the differential sinking of the ground surface with respect to surrounding terrain or sea level. It occurs when mineral resources are extracted or underground mining activities take place. Subsidence has serious effects the natural and built environment. It causes floods, reduces crop production, leads to soil loss and damages buildings (Bell, Stacey et al. 2000). Evidence of land subsidence has been found in the north central part of China and the mining areas of the country (Kuenzer, Zhang et al. 2007). According to Bian et al., (Bian, Inyang et al. 2010), mining ten thousand tons of raw coal will result in 0.2 hectares of subsiding land in China. Land subsidence in China also occurs due to increased urbanization and industrialization. China has 45 cities and municipalities where disastrous land subsidence has occurred with a total subsidence area of about 49,000 km^2, leading to 100 million Yuan in annual economic losses (Hu, Yue et al. 2004). Coincidentally, mining activities are found in the areas where land subsidence takes place due to urbanization as shown in Figure 6.

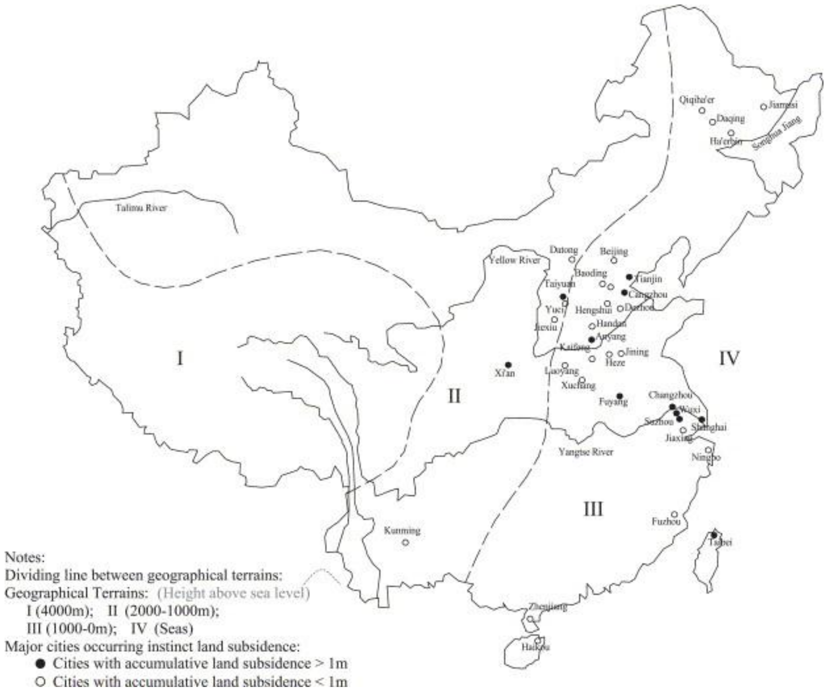

Figure 6: Land Subsidence in China

Source: (Hu, Yue et al. 2004)

2.5 Rail Transport

Coal is produced in the north and north-western parts of the country (Figure 7) but needed in the south-eastern areas. This makes transportation a key feature in China's coal framework which is primarily transported by rail. In 2008, coal made up 49% of China's railway commodity transportation (Mou and Li 2012). Indeed, one factor contributing to the recent rise in coal prices is stress from the transport system. Compared to oil and gas, the cost of coal transportation is much higher, and could account for up to 50% of the total coal price (Lin and Liu 2010). China's railroad cars are congested leading to competition for rail car capacity between coal and other commodities. The increase in coal transport by rail is surpassing rail track expansion, displacing other freight leading to a shift to road transport which is less efficient (Shealy and Dorian 2010). Interest in China's coal transportation system grew in the 1990s when coal consumption rose and pressure mounted on existing railroads to transport more coal. To cater for increasing demand, coal was transported by road, instigating a rise road congestion. This had spillover effects on the international market. In 2010, the Wall Street Journal reported that the traffic congestion that occurred in China in late 2010 caused an increase in local coal prices prompting the country to buy cheaper coal from the global markets, consequently raising international coal prices (Back 2010). These events stimulated an interest in studies relating to China's transportation network.[1] Findings by Paulus and Truby (2011) offered a solution to this problem – proposing that transportation costs could be lowered if coal was converted to electricity early in the supply chain, rather than transporting it via rail.

China has huge reserves of bituminous, anthracite, and lignite coal. According to the BP Statistical Review of World Energy 2009, Chinese proved coal reserves amount to 114.5 billion tons, or just under 14 percent of the world's total. Despite the abundance, China experienced coal supply shortages in 2003 and again in 2004 due largely to booming demand and inadequate rail infrastructure. While most of China's coal is produced in northern China, much of the demand is in the rapidly growing southern and eastern coastal provinces, requiring transport of coal over great distances.

Figure 7: China's coal deposits and major rail infrastructure

Source: (Shealy and Dorian 2010)

2.6 Deaths

Every year, China accounts for nearly 80% of the world's total coal related deaths, occurring from accidents. In China, the main causes of coal mine accidents are gas leaks, roof cave-ins, fires, blasts and floods (Yang 2007). These deaths occur in town and village enterprises (TVE's) which are generally small scale mines that often have no legal status and have poor safety standards. The TVE's play an important role in local development and provide employment to China's rural population, making it difficult for the Chinese government at all levels to enforce laws on mine safety. Figure 8 illustrates China's death rate in million tons coal production. Today, deaths have reduced and the study by Peng (2011) presents statistics on coal-related deaths in China. Between 1949 and 2009, 26 major accidents occurred where more than 100 people died in every accident. A majority of these accidents occurred due to human error and gas explosions. Most occurred in government owned

---

[1] For a review of the literature, please refer to Mou, D. and Z. Li (2012). "A spatial analysis of China's coal flow." Energy Policy(In Press).

facilities while others took place in self employed and private mines. The economic losses caused by fatal accidents and occupational diseases are huge. For every accident coal mines pay considerable amounts of money for rescue and treatment. They also compensate the families' kin. According to data of some mining bureaus, every accident with 1-fatality results in direct and indirect loses of about 300,000 Yuan (Shujie 2005).

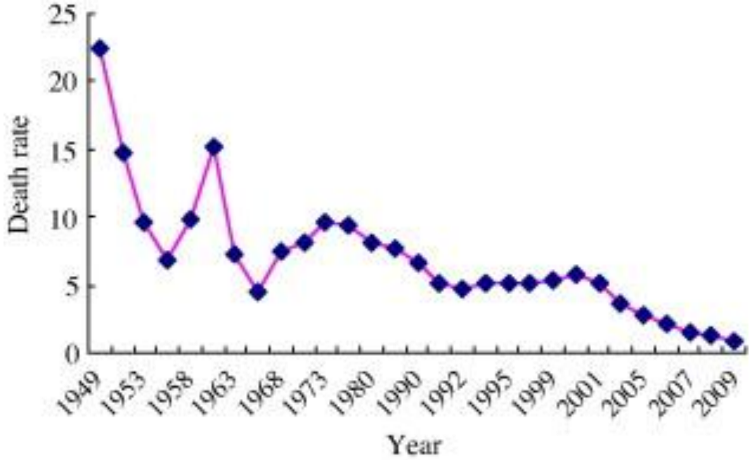

Figure 8: China's Death rate in million tons coal production from 1949 to 2009
Source: (Wu, Jiang et al. 2011).

3 MODEL

3.1 Spatial Panel Data Models

In this study, the relationship between coal production and the environmental effects of coal production are studied. Regional data will be used to capture each provinces' characteristics based on the literature discussed in the previous section. Econometric modeling techniques will then be applied to provide inference. LeSage (1997) found that practitioners engaged in statistical work with regional data samples should try considering spatial configuration in their work. It has also been realized that geographical factors play an important role in determining the effects of public policy (Lacombe 2004). Spatial autocorrelation in studying the effects of the environment on coal production can occur in many contexts. Coal producing areas are not bounded by the administrative boundaries we know. For example, Figure 7 shows "pockets" of coal deposits which have their own boundaries, different from provincial boundaries. Furthermore, environmental ramifications of coal production such as air pollution, land subsidence and flooding occur in areas transcending administrative boundaries. Studies wishing to account for these spatial qualities require the use of proxies to capture the impact of space. To make the proxies operational, a set of geographic boundaries must be assumed where clustering of the environmental effects occur. These boundaries may not be the same boundaries used by data collectors. This makes it virtually certain that spatial econometric techniques should be employed. Ignoring the spatial configuration of sample observations in regression analysis is known to contribute to spatial autocorrelation (Dubin 1998).

This study employs time series observations of Chinas provinces from 1996 to 2010. Spatial panels refer to data containing time series observations of a number of spatial units. Panel data is used in this study because it captures the changes in landscapes over time. There is also less collinearity among variables when panel data is employed. Finally, panel data present the opportunity of having more degrees of freedom which increase efficiency in estimation[2] (Elhorst 2010). The spatial units used are China's 31 provinces. Data is collected for the years 1996 – 2010. With, N=31 and T=16, the number of observations is 496. Before exploring our empirical results, we offer a brief review of spatial panel models.

3.2 Standard Models for Spatial Panels[3]

A simple pooled linear regression model with spatial specific effects is considered, without spatial interaction effects.

$$y_{it} = x_{it}\beta + \mu_i + \varepsilon_{it} \tag{1}$$

Where i is an index for the cross-sectional dimension which are provinces, with $i = 1,\ldots,N$ and t is an index for the time dimension (years), with $t = 1,\ldots,T$. y_{it} is coal production at province i in and year t , x_{it} an $(1, K)$ row vector of observations on the independent variables, and β a matching $(K,1)$ vector of fixed but unknown parameters. ε_{it} is an independently and identically distributed error term for i and t with zero mean and variance σ^2 , while μ_i denotes the spatial specific effect. The spatial effects control for all space–specific time invariant variables whose omission could bias the estimates in a cross-sectional study. When specifying the interaction between provinces, the model may contain spatial interaction in the dependent, independent variable, or both.

The spatial lag model (spatial autoregressive model – SAR) is structured to control for spatial autocorrelation or dependence in the dependent variable and geographic neighboring units. In our study, coal production in one region may affect coal production in a neighboring region. This may occur through competition amongst neighboring provinces, or situations where conditions in these areas favor certain patterns of coal extraction and production. Policies, culture or topographic conditions in

---

[2] The spatial panel codes used in this study are those developed by Paul Elhorst outlined in his website: <http://www.regroningen.nl/elhorst/> The software employed is Matlab version 7.

[3] This section of the paper heavily borrows material from Elhorst, P. (2010). Spatial Panel Data Models. Handbook of Applied Spatial Analysis,. G. A. E. Fischer MM. Berlin Heidelberg New York, Springer: 377-407.

neighboring provinces may encourage increased coal production. Thus, the SAR model is specified below:

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{ij} + x_{it}\beta + \mu_i + \varepsilon_{it} \tag{2}$$

Where δ is the spatial autoregressive coefficient and w_{ij} is an element of a spatial weights matrix W is a (31×31) first order contiguity weight matrix.

The spatial error model (SEM) controls for spatial autocorrelation in the dependent variable. A SEM model implies unobserved spatial dependence, which if unaccounted for could affect the precision of the coefficient estimates. In other words, if spatial dependence is present in the error terms then the standard errors would be downwardly biased in an OLS framework. The SEM model is specified as follows

$$y_{it} = x_{it}\beta + \mu_i + \phi_{it} \tag{3}$$

$$\phi_{it} = \lambda \sum_{j=1}^{N} w_{ij} \varphi_{it} + \varepsilon_{it}, \tag{4}$$

where ϕ_{it} denotes the spatially autocorrelated error term and λ the spatial autocorrelation coefficient.

The third specification is the Spatial Durbin model (SDM) in which there is spatial dependence in the dependent variables and the independent variable. An unconstrained SDM model with spatial fixed effects takes the form:

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{ij} + x_{it}\beta + \sum_{j=1}^{N} w_{ij} x_{ijt} \gamma_{it} + \mu_i + \varepsilon_{it}, \tag{5}$$

where γ is a $(K,1)$ vector of fixed but unknown parameters. The hypothesis $H_0 : \gamma = 0$ can be tested to investigate whether this model can be simplified to SAR, and the hypothesis $H_0 : \gamma + \delta\beta = 0$ can be tested to investigate whether the model can be simplified to the SEM. Maximum likelihood models are used to estimate models of this nature which include spatial interaction effects.

3.3 The Data Generating Processes for the models are as follows:

Fixed effects spatial lag model: The log likelihood function of model (2) with respect to β, δ and σ^2, if the spatial specific effects are assumed to be fixed is:

$$LogL = -\frac{NT}{2}\log\left(2\pi\sigma^2\right) + T\log\left|I_N - \delta W\right| - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it}^* - \delta\left[\sum_{j=1}^{N} w_{ij} y_{jt}\right]^* + x_{it}^*\beta - \mu_i\right)^2 \tag{6}$$

Where the second term on the right-hand side represented the Jacobian term. The asterisk denotes a demeaning procedure introduced on pp:7 (Elhorst). The log likelihood of the fixed effects spatial error eodel (3) if the spatial specific effects are assumed to be fixed is:

$$LogL = -\frac{NT}{2}\log\left(2\pi\sigma^{2}\right) + T\log\left|I_{N} - \delta W\right| - \frac{1}{2\sigma^{2}}\sum_{i=1}^{N}\sum_{t=1}^{T}\left\{ y_{it}^{*} - \rho\left[\sum_{j=1}^{N} w_{ij} y_{jt}\right]^{*} - \left(x_{it}^{*} - \rho\left[\sum_{j=1}^{N} w_{ij} x_{jt}\right]^{*}\right)\beta \right\}^{2} \tag{7}$$

3.4 Lagrange Multiplier Tests

The Lagrange Multiplier tests were developed by (Anselin, 1996) to test for spatially lagged dependent variable, spatial error correlation and their robust counterparts. The spatial panel LM tests are specified as follows:

$$LM_{\delta} = \frac{\left[e^{'}(I_{T} \otimes W)Y / \sigma^{2}\right]^{2}}{J} \quad \text{and} \quad LM_{\rho} = \frac{\left[e^{'}(I_{T} \otimes W)Y / \sigma^{2}\right]^{2}}{T \times T_{W}} \tag{8}$$

where the symbol $\otimes$ denotes the Kronecker product, I_T denotes the independent matrix and its subscript the order of this matrix. e denotes the residual vector of a pooled regression model without any spatial of time fixed effects or of a panel data model with spatial and/or time period fixed effects. Then, J and T_W are defined by:

$$J = \frac{1}{\sigma^{2}}\left[\left(\left(I_{T} \otimes W\right) X\beta\right)^{'}\left(I_{NT} - X\left(X'X\right)^{-1}X'\right)\left(I_{T} \otimes W\right) X\beta + TT_{W}\sigma^{2}\right], \tag{9}$$
$$T_{W} = tr(WW + W'W),$$

where the symbol tr denotes the trace of a matrix. The robust counterparts of these LM tests for a spatial panel are presented below:

$$\text{robust } LM_{\delta} = \frac{\left[e^{'}(I_{T} \otimes W)Y / \sigma^{2} - e^{'}(I_{T} \otimes W)e / \sigma^{2}\right]^{2}}{J - TT_{W}}, \tag{10}$$

$$\text{robust } LM_{\rho} = \frac{\left[e^{'}(I_{T} \otimes W)e / \sigma^{2} - TT_{W} / J \times e^{'}(I_{T} \otimes W)Y / \sigma^{2}\right]^{2}}{TT_{W}\left[1 - TT_{W} / J\right]} \tag{11}$$

4 EMPIRICAL RESULTS

Following the literature above, a model is designed to investigate the relationship between coal production, the environment, infrastructure, land use, and water. The dependent variable is coal production. The independent variables include a mixture of variables investigating a number of issues. Electricity generation is one of the main drivers of coal production in China. It is therefore included to analyze its effect on coal production.

The study also seeks to investigate the effect of the number of mining employees and their wages, on coal production. A lagged variable of wages is also included to investigate whether the previous year's wages impacted coal production. Past environmental events may influence coal production. For example, floods occurring in certain regions may affect coal production in the future. Lee (2011) reported that the flooding that occurred in Shanxi in 2011 caused deaths. This caused temporary suspension of underground mining as the mines had to be inspected, ultimately, leading to reduction in total output of coal. Therefore, variables capturing flooding, land subsidence and water logging were included in the analysis to investigate these effects. The model also includes lagged values of SO2 emissions to investigate their role on coal production.

Water is an issue in China, therefore, a lagged variable of discharge and treatment of waste water, captures the effect of the previous period's waste water on coal production. This variable is included for exploratory purposes and no priori hypothesis has been laid out for investigation. Then, the impact of transportation is investigated where present and lagged values of road and rail length are included. Further, the influence of technology on coal production is investigated. The number of patents granted is used as a proxy for measuring technological progress. This variable is lagged to capture the previous year's influence on coal production. A summary of the variables used is listed in the table below:

Variable(Period: 1996-2010)	**Units**
Coal Production	10000 tons
Total Volume of waste water discharge	10000 tons
Length of railway	10000 Km
SO2 Emissions	10000 tons
Technology – Number of Patent Granted	Units
Length of roads	10000 Km
Average Wage of a worker in the mining and quarrying industry	Yuan
Mining and Quarrying employees	10,000 persons
Area covered by flooding, waterlogged, landslides, debris flow	1000 ha
Electricity Production	100 million Kwh

Table 1: Summary of Values and Units

To estimate the results, MATLAB 9.1 is used together with the Spatial Econometric Toolbox developed by James LeSage. The results obtained from the SEM and SAR models are estimated using maximum likelihood techniques. However, model specification needs to be carried out to enable us to select one of the models for inference. To do the estimation, the Panel Lagrange Multiplier (LM) test for specification was employed (Elhorst 2010). According to the classic tests, the SAR model had a

Lagrange Multiplier value of 277.838 while the SEM had a value of 273.331. These results obtained through the classical approach were confirmed by the powerful robust test which found that SAR model as the preferred one of the two.

LM Lag Test for Omitted Spatial Autoregressive Model (SAR)	
LM value	277.8381
Marginal Probability	0.0000
Chi(1) .01 value	6.6400
LM Error Test for Omitted Spatial Error Model (SEM)	
LM value	273.3306
Marginal Probability	0.0000
Chi(1) .01 value	6.6400
Robust LM Spatial Autoregressive Model (SAR)	
LM value	21.4931
Marginal Probability	0.0000
Chi(1) .01 value	6.6400
Robust LM Spatial Error Model (SEM)	
LM value	16.99286
Marginal Probability	0.0000
Chi(1) .01 value	6.6400

Table 2: Lagrange Multiplier Test Results

4.1 SAR Results

Variables	Direct	Indirect	Total
electricity generation	**6.9627**	**4.8715**	**11.8342**
	(8.9520)* **	**(4.4579)*** **	**(7.3317)*** **
number mining employees	**1.5961**	**1.1177**	**2.7138**
	(1.9110)*	**(1.7616)***	**(1.8825)***
mining wages	**-0.1127**	**-0.0790**	**-0.1917**
	(-3.4838)* **	**(-2.8080)*** **	**(-3.3251)*** **
lag_mining wages	**0.0875**	**0.0613**	**0.1487**
	(3.0240)* **	**(2.5757)*** **	**(2.9380)*** **
lag_SO2 emissions	-0.0019	-0.0013	-0.0033
	(-0.7379)	(-0.7079)	(-0.7299)
lag_area covered by flooding	**1.2940**	**0.9052**	**2.1991**
	(1.7729)*	**(1.6504)***	**(1.7500)***
lag_volume of waste water discharge	**-0.0418**	**-0.0293**	**-0.0711**
	(-5.3342)* **	**(-3.7032)*** **	**(-4.9330)*** **
road length	17.3470	12.1165	29.4634
	(-1.3700)	(-1.2953)	(-1.3548)
lag_road length	16.1666	11.3577	27.5243
	(-1.1941)	(-1.1177)	(-1.1737)
rail length	5.4717	3.8798	9.3515
	(-0.3925)	(-0.391)	(-0.3939)
lag_rail length	-15.5917	-10.9761	-26.5678
	(-1.0752)	(-1.0389)	(-1.0703)
lag_patents granted	**-0.0520**	-0.0365	**-0.0885**
	(-1.7163)*	(-1.5891)	**(-1.6893)***
W*dep.var	0.4346		
	(8.3343)***		
R^2	0.5788		
Log-Likelihood	-5023.0947		

(Note: ***, ** & * denotes level statistical significance at 1%, 5% and 10%, respectively. Number in brackets represents t-stat.)

Table 3: Results from the SAR Model

Table 3 shows the direct, indirect[4] and total effects estimates of the SAR. The second column presents the direct effect estimates which relay the impacts of the variables on their own-province's coal

---

[4] The direct effects (average row effect) quantifies the impact on a particular element of the dependent variable as a result of a unit change in all elements of an exogenous variable, while the indirect effect (average column effect) quantifies the impact of

production, plus feedback effects. The indirect effect estimates presented in the third column reflect the effects of the variables on coal production in neighboring provinces. The sum of the direct and indirect effects give the total effects estimates. These estimates reflect the variable's effect on its own-province plus the (average) cumulative sum of impacts on all other counties as well (Kirby and LeSage 2009).

- The degree is spatial dependence is 0.43 and statistically significant indicating a level of spatial autocorrelation in the regression relationship.
- The direct, indirect and total effects of electricity generation are significant within the 1% level of significance. Increasing electricity generation by 100 million KwH in a province raises coal production by 69,627 tons[5] within the province and 48,715 tons to neighboring provinces. The total effect is an increase of 118,342 tons in China.
- The direct and indirect and total effects of mining employees are significant within the 10% level of significance. Increasing mining employees within a province by 10,000 increases coal production by 15,961 tons within that province and 11,177 tons in neighboring provinces.
- The direct, indirect and total effects of wages are significant within the 10% level of significance. Increasing mining workers' wages by 1 Yuan in a province reduces coal production by 1,127 tons within that province. The indirect and total effects of this increase are 790 and 1,917 tons respectively.
- Surprisingly, the lagged value of mining wages produces a positive effect on coal production, producing direct and indirect effect of 875 and 613 tons of coal due to an increase in wages by 1 Yuan. The total effects due to this increase are 1,487 tons to the country.
- The previous years' flooding positively causes an increase in coal production within the 10% level of significance. Increasing flooding[6] by 1000 ha in a province causes coal production to increase by 12,940 tons, while indirect and total effects are 9,025 and 21,991 tons. This may mean that incidences that occurred last year may have suspended coal production for a while, before resumption in production in the next year which was accompanied by a boost in coal production.
- An increase in discharge in last year's waste water reduces coal production. The direct, indirect and total effects estimates are significant within a 1% level of significance. A 1000 ton increase in waste water in a province reduced coal production by 418 tons within provinces and 293 tons in neighboring province. The total effects are a total reduction of 711 tons of coal produced in China.
- Finally, pertaining to technology, increasing the previous years' number of patents granted, reduced coal production by 885 tons in China.

---

changing a particular element of an exogenous variable on the dependent variable of all other units. The direct effects of the explanatory variables are different from their coefficient estimates due to feedback effects that arise as a result of impacts passing through neighboring provinces and back to the provinces themselves.

[5] 6.9627*10000 tons

[6] Includes area covered by waterlogged, landslides and debris flow

4.2 SDM Results

LeSage and Pace (2009) recommend that the spatial Durbin model produces unbiased coefficient estimates when compared to other models. SDM extends the spatial lag model with spatially lagged independent variables. The SDM results are presented and compared to the SAR estimates presented above.

Variables	Direct	Indirect	Total
electricity generation	**7.6889**	-2.6623	**5.0265**
	(9.1543)***	(-0.9378)	**(1.6574)***
number mining employees	1.2843	-2.9250	-1.6407
	-1.4004	(-0.8200)	(-0.4031)
mining wages	**-0.1388**	-0.1344	**-0.2732**
	(-3.7562)***	(-0.9242)	**(-1.6457)***
lag_mining wages	**0.1027**	0.1274	0.2302
	(3.0240)***	(-0.8905)	(1.3956)
lag_SO2 emissions	-0.0011	0.0100	0.0089
	(-0.3704)	(-0.8436)	(0.6534)
lag_area covered by flooding	1.3188	-0.4759	0.8429
	(-1.6209)	(-0.1449)	(0.2243)
lag_volume of waste water discharge	**-0.0401**	-0.0258	**-0.0659**
	(-4.9020)***	(-0.9349)	**(-2.2346)****
road length	15.2594	25.748	41.0074
	(-1.0694)	(-0.4808)	(0.6583)
lag_road length	**24.0807**	**107.5265**	**131.6072**
	(1.7047)*	**(1.9083)***	**(2.0224)***
rail length	-0.4023	-6.7745	-6.3721
	(-0.0259)	(-0.1065)	(-0.0870)
lag_rail length	-16.2736	17.3498	1.0762
	(-1.0037)	(-0.2566)	(0.0138)
lag_patents granted	-0.044	-0.0687	-0.1127
	(-1.4875)	(-0.6161)	(-0.8969)
W*dep.var	**0.4488**		
	(8.2752)***		
R2	0.5964		
Log-Likelihood	-5013.4682		

(Note: ***, ** & * denotes level statistical significance at 1%, 5% and 10%, respectively. Number in brackets represents t-stat.)

Table 4: Results from the SAR Model

Table 4 presents the direct, indirect and total effects estimates of the SDM model

- The degree of spatial dependence is 0.44 and statistically significant indicating a level of spatial autocorrelation in the regression relationship.
- The direct and total effects of electricity generation are significant within the 1% and 10% level of significance. Increasing electricity generation by 100 million KwH increases coal production by 76,889 tons within the province and 50,265 tons in China.
- The direct and total estimates of mining wages are significant at the 1% and 10% levels respectively. Increasing wages by 1 Yuan decreases coal production within the province by 1,388 tons and 2,732 tons in the country.
- However, lagged values of mining wages impart a direct, positive influence on coal production within 1% level of significance.
- Increasing the previous years' waste water discharge by 1000 tons reduces coal production by 401 tons within the province while the total effect is a reduction of 659 tons. The reason for this is that coal producers are realizing these negative effects of waste, instigating a reduction in coal production.
- Finally, the direct, indirect and total effects of the lagged value of road length are significant within the 1% level of significance. Increasing road length by 1000 km increases coal production by 240,807 tons within the province and 1.3 million tons in the country. These results indicate that it takes coal producers a while to re-align their supply chain and sale patterns to get their coal to destinations.

5 CONCLUSIONS

This study employs provincial level data to investigate the relationship between coal production and various factors in China. The Spatial Autoregressive model and Spatial Durbin Model are employed to examine the effects of demand, the environment, employees, wages and technology on coal production. The results from the marginal effects estimates presented new findings on coal production in provinces is affected by factors within their provinces. They also shed light on how factors in neighboring provinces affect its production.

- *The results from the SAR model provide useful insights. From the demand side electricity generation has the greatest effect on coal production while the effect of last year's waste water discharged has the greatest impact on coal production from an environmental point of view. Surprisingly, the transportation sector did not impact coal production.*
- *The results from the SDM show that electricity generation is the greatest influence on coal production. Further, increasing road lengths increases coal production while increasing mining wages reduces coal production.*

- *The similarity between the two models is that electricity production has the greatest influence on coal production. Furthermore, mining wages and waste water affect coal production. They also detect the presence of spatial autocorrelation in the model.*
- *The difference between the two is that the SDM picks up the importance of road length in coal production while SAR acknowledges the influence of the number of employees and technology in production.*
- *These results make us realize the importance of electricity generation and wages on coal production in China.*

From a policy stand point, policy makers in China ought to consider the electricity production as a main driver to driving coal production. Hence, to reduce the negative environmental effects of coal production, other sources of energy should be incorporated into the grid to feed the rising demand for electric power.

The weakness of this study stems from the data used. First, for the number of mining employees and wages, encompass all the mining industries. Furthermore, flooding, waterlogged, landslides and debris flow could be caused by external factors such as urbanization or natural occurrences. These variables are proxies aimed at modeling similar scenarios in the coal mining industry and may not accurately reflect what is happening in the industry. Nevertheless, given the paucity of China related data, this study uncovers novel results related to coal production.

References

Back, A. (2010). Quicker Growth Predicted for China The Wall Street Journal. New York.

Bell, F. G., S. E. T. Bullock, et al. (2001). "Environmental impacts associated with an abandoned mine in the Witbank Coalfield, South Africa." International Journal of Coal Geology **45**(2–3): 195-216.

Bell, F. G., T. R. Stacey, et al. (2000). "Mining subsidence and its effect on the environment: some differing examples." Environmental Geology **40**(1): 135-152.

Bian, Z., J. Dong, et al. (2009). "The impact of disposal and treatment of coal mining wastes on environment and farmland." Environmental Geology **58**(3): 625-634.

Bian, Z., H. I. Inyang, et al. (2010). "Environmental issues from coal mining and their solutions." Mining Science and Technology (China) **20**(2): 215-223.

Cantú, N. (2005). Towards a Sustainable Energy Production: A study and comparison of the coal and biomass energy production systems. International Environmental Science. Lund, Sweden, Lund University. Master's Programme in International Environmental Science: pp: 1-44.

Dubin, R. A. (1998). "Spatial Autocorrelation: A Primer." Journal of Housing Economics **7**(3): 304-327.

Elhorst, P. (2010). Regional Science Groningen. Groningen, University of Groningen **2011**.

Elhorst, P. (2010). Spatial Panel Data Models. Handbook of Applied Spatial Analysis,. G. A. E. Fischer MM. Berlin Heidelberg New York, Springer**:** 377-407.

Haibin, L. and L. Zhenling (2010). "Recycling utilization patterns of coal mining waste in China." Resources, Conservation and Recycling **54**(12): 1331-1340.

Hu, R. L., Z. Q. Yue, et al. (2004). "Review on current status and challenging issues of land subsidence in China." Engineering Geology **76**(1–2): 65-77.

Hubacek, K., D. Guan, et al. (2009). "Environmental implications of urbanization and lifestyle change in China: Ecological and Water Footprints." Journal of Cleaner Production **17**(14): 1241-1248.

International Energy Agency (2009). Cleaner Coal in China. Paris, France, Stedi Media**:** pp:1-322.

Kirby, D. K. and J. P. LeSage (2009). "Changes in commuting to work times over the 1990 to 2000 period." Regional Science and Urban Economics **39**(4): 460-471.

Kuenzer, C., J. Zhang, et al. (2007). "Uncontrolled coal fires and their environmental impacts: Investigating two arid mining regions in north-central China." Applied Geography **27**(1): 42-62.

Lacombe, D. (2004). "Does Econometric Methodology Matter? An Analysis of Public Policy Using Spatial Econometric Techniques." Geographical Analysis **36**(2).

Larssen, T., H. M. Seip, et al. (1999). "Acid deposition and its effects in China: an overview." Environmental Science & Policy **2**(1): 9-24.

Lee, I. (2011). "Flooding in Shanxi coal mines affect China Coal's production by half each month." Metals and Mining, Asia. Retrieved August, 2012, 2012, from http://www.nomuranow.com/research/globalresearchportal/GetPub.aspx?pid=463640.

LeSage, J. P. and R. K. Pace (2009). Introduction to spatial econometrics, CRC Press.

LeSage, P. J. (1997). "Regression analysis of spatial data." Regional Analysis and Policy **27**(2): 83-94.

Lin, B.-q. and J.-h. Liu (2010). "Estimating coal production peak and trends of coal imports in China." Energy Policy **38**(1): 512-519.

Liu, J. and J. Diamond (2005). "China's environment in a globalizing world." Nature **435**(7046): 1179-1186.

Meng, L., Q.-y. Feng, et al. (2009). "Environmental cumulative effects of coal underground mining." Procedia Earth and Planetary Science **1**(1): 1280-1284.

Minchener, A. J. (2005). Coal in China. Energia. Center for Applied Energy Research. Lexington, University of Kentucky. **16:** pp:1-6.

Moore, M. (2011). China's coal rush leaves three million living on the edge. The Telegraph. London.

Mou, D. and Z. Li (2012). "A spatial analysis of China's coal flow." Energy Policy(In Press).

Netherlands Environmental Assessment Agency (2007) China now no. 1 in CO_2 emissions; USA in second position.

Parker, S. (2004). Coal. Gareth Stevens Publisher. New York.

Paulus, M. and J. Trüby (2011). "Coal lumps vs. electrons: How do Chinese bulk energy transport decisions affect the global steam coal market?" Energy Economics **33**(6): 1127-1137.

Peng, W. (2011). "Coal sector reform and its implications for the power sector in China." Resources Policy **36**(1): 60-71.

Schweinfurth, S. P. (2005). "Coal—A Complex Natural Resource." Retrieved 2011, 2005, from http://pubs.usgs.gov/circ/c1143/html/text.html.

Shealy, M. and J. P. Dorian (2010). "Growing Chinese coal use: Dramatic resource and environmental implications." Energy Policy **38**(5): 2116-2122.

Shujie, Y. (2005). Some Aspects of the Coal Industry Sustainable Development in China. Cracow - Szczyrk - Wieliczka, Poland, Taylor & Francis 2005.

Su, S., B. Li, et al. (2011). Sulfur Dioxide Emissions from Combustion in China: From 1990 to 2007. Environmental Science and Technology. American Chemical Society Publications. Beijing, Peking University**:** pp: 1-8.

Sun, W., Q. Wu, et al. (2012). "Avoiding Coal–Water Conflicts During the Development of China's Large Coal-Producing Regions." Mine Water and the Environment **31**(1): 74-78.

The World Bank (2007). Cost of Pollution in China: Economic Estimates of Physical Damages. Washington, D.C., The World Bank. Conference Edition: pp: 1-151.

US Energy and Information Administration (2010). "Country Analysis Briefs, China." Retrieved July 5, 2012, from http://www.eia.doe.gov/cabs/China/Coal.html.

Vince, G. (2012). Can China create the solutions to our energy problems? BBC. London.

World Coal Association (2012). Coal Statistics, World Coal Association. Accessed on July, 2012 from http://www.worldcoal.org/resources/coal-statistics/.

Wu, L., Z. Jiang, et al. (2011). "Major accident analysis and prevention of coal mines in China from the year of 1949 to 2009." Mining Science and Technology (China) **21**(5): 693-699.

Yang, Y. (2007). Coal Mining and Environmental Health in China. Proceedings of the China Environment Forum's Partnership with Western Kentucky University on the USAID. Coal Industry Press**:** pp: 1-6.

Zhu, W. and D. Sethuraman (2012). China Coal Imports Rise 90% In April, Coal Association Says. Bloomberg. New York City, Bloomberg L.P.