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R&D Status and the Performance of Domestic Firms in China's Coal Mining Industry

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Abstract

Coal use accounts for a very large proportion of electricity production in China. Using a recently developed coarsened exact matching (CEM) technique, this paper examines the impact of research and development (R&D) activities on the performance of firms in China's coal mining industry. Our empirical results reveal that firms in China's coal industry that conduct R&D are more productive and their sales are higher. However, as far as the firm profitability and market shares are concerned, whether or not a firm in China's coal industry conducts R&D makes no difference. We find that foreign direct investment in China's coal mining industry leads to a significant decrease in the market share of domestic firms and its impact on productivity, sales and profitability of domestic firms is insignificant. The empirical results presented in this paper suggest that policies that encourage domestic firms in China's coal mining industries to conduct R&D can increase domestic production thereby reducing reliance on imports. Furthermore, productivity gains arising from R&D activities can also help Chinese mining firms to improve their competitive position in the international market. However, there is a need for restricting foreign direct investment in China's coal mining industry.

Key Words: R&D activities, coal mining industry, productivity, Coarsened exact matching, China

1. Introduction

During the past few decades, China's economy has experienced phenomenal growth. As a result of this growth, China's demand for natural resources such as coal has significantly increased.[1] Coal is a major source of electricity generation. The rising demand for coal is being satisfied through an increase in domestic production and imports.[2] An increase in China's demand for coal has implications for the environment. In order to build an innovation-based economy, the Chinese government is encouraging research and development (R&D) in all sectors of the economy, including sectors that contribute to energy sources. Table 1 shows the estimated pair-wise linear correlation coefficients involving GDP, production and import of coal. The top panel of Table 1 is the correlation between level variables while the bottom panel shows the correlation between the growth rates. The top panel shows that there is a strong relationship between (i) coal production and GDP and (ii) coal imports and GDP. The bottom panel suggests that the growth rate of imports is negatively related to GDP but this relationship is very weak.

<insert Table 1 here>

While a number of existing studies have explored the impact of R&D on productivity in China, relatively few studies have focused on China's coal mining industry.[3] This paper examines the impact of R&D spending on productivity in China's coal mining industry.

[1] Using industry level data, Bloch, Rafiq and Salim (2015) conclude that coal use has contributed to China's economic growth but it is also associated with increase in pollution. In an earlier study using Vector Error Correction methodology, Bloch, Rafiq and Salim (2012) have shown that coal consumption in China causes significant increase in pollution.

[2] From 1996 to 2010, the average annual growth of GDP and coal production respectively was 9.87 and 6.01 per cent. During the same period, the imports of coal grew on average by 50.55 per cent. From 1995 to 2010, the GDP index of China registered more than a four-fold increase and during the same period, there has been a rapid increase in coal production. There seems to be a close link between China's economic growth and consumption of natural resources (China Mining, 2013). Coal is widely used for electricity production in China and hence China's rapid economic growth depends heavily on coal production and imports.

[3] For example, the empirical work of Jefferson *et al.* (2006), Li *et al.* (2007) and Yang *et al.* (2010) suggests that R&D spending has a positive impact on productivity in China's manufacturing sector. In a recent study, Sheng and Song (2013) re-estimated the total factor productivity (TFP) of firms in China's iron and steel industry.

Analysis of the impact of R&D spending on firm performance in China's coal mining sector allows one to develop a better understanding of production and import of coal in China. An increase in the production of coal can reduce its dependence on imports. The analysis presented in this paper is based on a recently developed coarsened exact matching technique, which allows one to isolate the impact of R&D on firm performance. The technique involves matching firms that are involved in R&D activities with firms that are not involved in R&D activities. As a result of the matching, an appropriate control group is created, which allows a relatively more accurate comparison of firm performance based on their R&D status. We consider four indicators of firm performance in China's coal mining sector; productivity, sales, profitability and market share.

The rest of the paper is organized as follows. Section 2 contains a review of the related literature. Section 3 contains a discussion of the methodology. Empirical results are presented in Section 4. Section 5 includes a discussion of the empirical results. The last section contains some concluding remarks and policy implications.

2. Review of the Related Literature

A number of previous studies have focused on various aspects of coal mining industry in China. One strand of the existing studies focus on the demand for coal in China Using income, price and relative size of the heavy industry as the main determinants of demand, Chan and Lee (1997) attempted to forecast the demand for coal in China. Cattaneo et al. (2011) considered the coal demand at the provincial level. Their work suggests that on average demand for coal in China will increase by 2 per cent per year.[4]

[4] Crompton and Wu (2005) used a vector autoregression model to investigate the energy consumption in China. Their work suggests that demand for coal in China would increase on average by 3.3 per cent per year over the period 2004-2010.

Li and Leung (2012) examined the impact of coal consumption on economic growth in China. They find that coal consumption Granger causes the GDP in both Coastal and Central China. Due to its importance and the significant pollution it generates, some studies explore the environmental aspect of coal consumption. Shi (2011) suggests that coal consumption can be reconciled with the environment via declined emission intensity. After reviewing the development of clean coal technology in China, Chen and Xu (2010) report that China has achieved some success in these technologies. Zhang et al. (2011) believe that a coal-resource integration project in Shanxi Province of China has contributed to energy saving and emission reduction.

Few available studies appear to have focused on the production side. Wang et al. (2011), Lin and Liu (2010) and Wang, Feng and Tverberg (2013), among others, attempt to forecast China's coal production. Shen et al. (2012) highlight the importance of appropriate policy development in China's coal industry. In summary, earlier studies on China's coal mining industry mostly focus on the demand side. This paper focuses on the supply side – specifically, the supply from domestic sources.

3. Methodology and Data

In order to examine the impact of R&D activities on firm performance in China's coal mining industry, we employ a recently developed coarsened exact matching (CEM) technique. This technique is particularly useful when some independent variables are subject to endogeneity problem. A brief description of this technique is presented below.

Let an indicator variable $drd_{it} \in \{0,1\}$ denote whether a firm conducts R&D, which takes a value of one if firm *i* conducts R&D at time *t* and zero otherwise. We can measure the effectiveness of R&D as the impact it exerts on the firm performance, which in turn can be defined as:

$$\pi_{it} = p_{it}^{1} - p_{it}^{0} \quad (1)$$

where p_{it}^{1} is the performance of firm *i* at time *t* that conducts R&D and p_{it}^{0} is the performance of the same firm if it does not conduct R&D.

Equation (1) measures the net improvement in the performance of firm *i* due to R&D spending at time *t* difference. In empirical studies, whether or not a firm conducts R&D can be measured by a dummy variable drd_{it} that takes a value of 1 if the *i*th firms conducts R&D and zero otherwise $(drd_{it} = 0)$. However, equation (1) is not identified in that in real life a firm either conducts or do not conduct R&D. In other words, in real life, either p_{it}^{1} or p_{it}^{0} will be observed. Following the existing studies, in order to overcome this difficulty, we focus on the average treatment effect (see for example, Heckman *et al.* 1997; Dehejia and Wahba 2002) as follows:

$$E\left\{p_{it}^{1} - p_{it}^{0} \middle| drd_{it} = 1\right\} = E\left\{p_{it}^{1} \middle| drd_{it} = 1\right\} - E\left\{p_{it}^{0} \middle| drd_{it} = 1\right\} \quad (2)$$

In equation (2), the average performance if firm *i* does not conduct R&D, $E\left\{p_{it}^{0} \middle| drd_{it} = 1\right\}$, is unobserved. After controlling for possible self-selection bias due to factors that affect both the R&D decision and firm performance, namely with an appropriate counterfactual comparison group, we can estimate $E\left\{p_{it}^{0} \middle| drd_{it} = 1\right\}$ by $E\left\{p_{it}^{0} \middle| drd_{it} = 0\right\}$.

We construct the comparison group by making use of CEM proposed by Iacus, King and Porro (2011). Under the unconfoundedness assumption, i.e., conditional on observable factors, the outcome (i.e., firm performance) is independent of the treatment (R&D). The CEM algorithm first coarsens each factor and groups the factor into categories in which the factor has substantively indistinguishable values.[5] In the next stage, the algorithm stratifies the data by categories created in the coarsening. At every stratum, CEM matches treated firms (i.e., firms that conduct R&D) to non-treated firms (i.e., firms that do not conduct R&D) to create an appropriate comparison group. Once the comparison group has been created, the uncoarsened data of matched observations are used to estimate the treatment effect (i.e., the impact of R&D).

For a comparison group to be appropriate, its distribution of the factors shall be similar to those of treated groups - i.e., the imbalance between them must be small. In order to measure the imbalance, Iacus, King and Porro (2011) propose a $L_1 - type$ distance. This involves discretizing and cross-tabulating the factors used in the coarsening and counting the *k*-dimensional relative frequency, where *k* is the number of factors used in the coarsening process. The measurement of imbalance involves summation of the frequencies as follows:

$$L_1(f,g) = \sum_{l_1 \cdots l_k} \left| f_{l_1 \cdots l_k} - g_{l_1 \cdots l_k} \right| \qquad (3)$$

where *f* and *g* respectively are the treated and the control units; $l_1 \cdots l_k$ are the number of bins used in the discretization or levels of categorical factors; L_1 takes ranges between 0 and 1, with 1 indicating a complete imbalance and 0 represents a complete balance. The CEM technique is implemented using a statistical package developed by Blackwell *et al.* (2008).

Once an appropriate comparison group has been created, we can use regression analysis to estimate the treatment effect.[6] The firm performance in this paper is measured by (i) productivity, (ii) sales, (iii) profitability and (iv) its market share. While the focus is on the

[5] Within the context of this paper, matching involves dropping some information from the dataset so that there is a better balance between firms that conduct R&D and firms that do not. Matching tends to reduce the confounding influence of control variables. Exact matching can totally eliminate this influence. Confounding influence can lead to spurious relationship. For further information, please see Iacus, King and Porro (2011 & 2012).

[6] The matching process serves to reduce the model dependence and hence simple regression can be used for further analysis (see Abadie and Imbens, 2011).

role of R&D spending on firm performance, both firm and industry specific variables are used as control variables. We use the following regression equations to estimate the impact of R&D on firm production, sales, profitability and market share as follows:

$$\begin{aligned}\ln(lp) = {} & \alpha_0 + \alpha_1 firmsize + \alpha_2 age + \alpha_3 k + \alpha_4 averagewage + \\ & \alpha_5 ownership + \alpha_6 western + \alpha_7 middle + \alpha_8 herfindahl + \\ & \alpha_9 oic + \alpha_{10} fdi + \alpha_{11} drd + u_1\end{aligned} \tag{4}$$

$$\begin{aligned}\ln(sales) = {} & \beta_0 + \beta_1 firmsize + \beta_2 age + \beta_3 k + \beta_4 averagewage + \\ & \beta_5 ownership + \beta_6 western + \beta_7 middle + \beta_8 herfindahl + \\ & \beta_9 oic + \beta_{10} fdi + \beta_{11} drd + u_2\end{aligned} \tag{5}$$

$$\begin{aligned}profitability = {} & \gamma_0 + \gamma_1 firmsize + \gamma_2 age + \gamma_3 k + \gamma_4 averagewage + \\ & \gamma_5 ownership + \gamma_6 western + \gamma_7 middle + \gamma_8 herfindahl + \\ & \gamma_9 oic + \gamma_{10} fdi + \gamma_{11} drd + u_3\end{aligned} \tag{6}$$

$$\begin{aligned}marketshare = {} & \lambda_0 + \lambda_1 firmsize + \lambda_2 age + \lambda_3 k + \lambda_4 averagewage + \\ & \lambda_5 ownership + \lambda_6 western + \lambda_7 middle + \lambda_8 herfindahl + \\ & \lambda_9 oic + \lambda_{10} fdi + \lambda_{11} drd + u_4\end{aligned} \tag{7}$$

where lp is labour productivity (i.e., the value added per worker in constant 2005 prices); *sales* is firm sales in 2005 prices; *profitability* is the firm profit to sales ratio; *marketshare* is the ratio of firm sales to the total 4-digit sub-industry sales; *u*'s are the error terms; *firmsize* is firm size (which is measured by the number of employees in thousands); *k* is capital intensity (i.e., fixed assets per employee); *averagewage*, which is a proxy for human capital, is total salary divided by the number of employees; *ownership* is a dummy variable and takes a value of 1 if a firm is privately owned; *western* and *middle* are two dummies and take a value of 1 if a firm is located in Western and Central China respectively; *herfdindahl* is the Herfindahl index (i.e., the sum of squared market share in the 4-digit sub-industries) which captures the impact of market structure in that a higher value represents a relatively more monopolistic market structure; *oic* is the overall industry concentration (i.e., the ratio of province-4-digit-industry share of national industry employment to province share of national manufacturing employment) which aims to capture the impact of industry concentration; *fdi* is foreign investment (which is approximated by the output share of foreign firm in the 4-digit sub-industries); and *drd* is a dummy variable, which takes a value of one if a firm conducts R&D and zero otherwise. *drd* is the main variable of interest - the rest of the variables control for the remaining imbalance between the treated and the control groups.

The empirical analysis presented in this paper is based on firm level data obtained from the enterprise survey from China National Bureau of Statistics. The sample covers the period of 2005-2007. The summary statistics presented in Table 2 shows substantial variations in the dataset. Some figures in Table 2 such as the minimum firm size are negative because firm size is measure in thousands of workers and the natural logarithm of a small proportion is negative.

<insert Table 2 here>

4. Empirical Results

As the focus of this study is on the role of R&D status of a firm within the coal mining industry, the coarsening is carried out over the domestic control variables that are included in equations (4) to (7). As foreign investment does not take place in all firms, we excluded foreign investment from the coarsening process. The CEM procedure generated 8,268 strata (i.e., sub-groups of data), where 224 strata were matched and 236 firms that conduct R&D are matched to 1,147 firms that do not conduct R&D.

<insert Table3 here>

Table 3 reports the reduction in the imbalance both before and after the matching. The overall L_1 decreases from 0.99 before matching to 0.85 after the matching in the coal mining industry. The individual L_1 also drops significantly after the matching, for example the L_1 of firm size decreases from 0.53 to 0.06 in the coal industry. After matching the difference between means of treated and control groups is almost completely eliminated, which suggests that the CEM technique is able to produce a reasonable match. Using the matched data, equations (4) to (7) are estimated by means of ordinary least squares.

5. Discussion

5.1 R&D and firm performance in China's Coal industry

The main aim of the empirical analysis is to examine the impact of R&D status on four measures of firm performance; productivity, sales, profitability and market share. The estimated coefficient of *drd* (whether a firm conducts R&D) measures the treatment effect. Table 4 shows that, within the coal mining industry, the estimated coefficient of *drd* in the productivity and sales regressions is positive and statistically significant. This suggests that R&D activities exert a positive impact on both labour productivity and sales. On average, as compared to the firms that do not conduct R&D, labour productivity and sales of firms that conduct R&D, respectively, are 0.27 and 0.03 per cent higher. As the estimated coefficient of *drd* in profitability and market share regression equations is insignificant, with a very high degree of confidence, it can be argued that R&D activities do not affect firm profitability and market share.

<*insert Tables 4 here*>

In over all terms, the results presented in Table suggest that the impact of R&D activities on at least 2 out of 4 firm performance measures in the coal mining industry is positive. As discussed earlier, R&D can be viewed as a knowledge production process where R&D contributes to knowledge production, which in turn improves firm productivity and sales. The enhanced productivity advantage from R&D can transmit to other aspects of firm performance. The empirical results presented in Tables 4 reveal that firm profitability is not affected by R&D activities. This result is somewhat surprising. However, most firms in China's coal industry are subsidiaries of their respective parent groups and hence these firms are not individually aiming to maximize their profits – the objective is to maximize the profit of the parent group.

5.2 The impact of control variables on firm performance

The results presented in in Table 4 suggest that firm size exerts a negative impact on labour productivity but its impact on firm sales and market share is positive. This appears to signal the absence of economies of scale in China's coal mining industry. Older firms in coal industry are less productive and profitable but their market share is higher. While older firm have more production experience, younger firms are more likely to embrace new technology and therefore the impact of firm age on the indicators of firm performance can be negative. Capital intensity has a positive effect on productivity, sales and market share, which is not surprising as the mining sector requires large investment. Average wage which is a proxy for human capital has a positive impact on firm productivity, sales and profitability. Privately owned mining firms are more productive and their market share is also higher. Firms located in western China are less productive. Furthermore coal mining firms in central and western china are less profitable.

The Herfindahl index, overall industry concentration, and FDI are 4-digit industry level variables. These variables control respectively for the impact of (i) market structure, (ii) spillovers from concentration of mining activities and foreign investment. Except for the impact on market share, the impact of Herfindahl index on productivity, sale and profitability is insignificant, which is not surprising as higher value of Herfindahl index is consistent with a relatively more monopolistic market structure.

The overall industry concentration does not appear to generate any significant impact in the coal industry. The estimated results presented in Tables 4 highlight the role that is played by foreign direct investment in China's coal mining industry. It seems that foreign direct invest does not significantly affect the productivity, sales and profitability of domestic firms. However, its impact on the market share of domestic firms is negative. While the impact of foreign investment on productivity in China's coal mining industry appears to be insignificant, there is a positive association between R&D status and firm productivity.[7]

6. **Concluding remarks and policy implications**

Rapid economic growth in China has resulted in an increase in demand for electricity. Approximately 81% of the electricity produced in China in 2013 was generated by coal (Coal Statistics, 2014). The increase in demand for electricity in China can be attributed to (a) an increase in demand for China's exports, which has necessitated the increase in its industrial production and (b) an improvement in the general standard of living, which has resulted in increase in demand for electricity for household use. As a result of increase in demand for electricity there is increase in demand for coal in China. In order to reduce its reliance on imports, Chinese government is encouraging domestic coal mining firms to conduct R&D and at the same time steps are taken to encourage foreign investment in the coal mining sector.

Using panel data from China over the 2005-2007 period and employing a recently developed coarsened exact matching technique, this paper focuses on the impact of R&D status on the performance of domestic firms in China's coal mining industry. We consider four measures of firm performance: productivity, sales, profitability and market share. The empirical results presented in this paper reveal that domestic coal mining firms that conduct

[7] Improvement in productivity through R&D investment increases domestic production, thereby reducing reliance on import of coal. Furthermore, such improvement in productivity also helps the Chinese firms to better compete with highly productive foreign firms.

R&D are relatively more productive. Specifically, firms that conduct R&D are on average 0.2717% more productive and these firms also experience a statistically significant increase in sales.

The empirical results presented in this paper suggest that China's policy of encouraging R&D in its mining sector is bearing fruit in that firms that conduct R&D are relatively more productive. Accordingly, the existing policies, such as the preferential tax rates, that encourage R&D are justified. An increase in the number of Chinese firms that conduct R&D increases domestic production, which can contribute to a decrease in China's dependence on import of coal. Foreign direct investment in China's coal industry does not appear to have contributed to a statistically significant impact on productivity, sales and profitability of domestic firms. Furthermore, foreign direct invest leads to a decline in the market share of domestic firms in China's coal mining industry. This suggests that there is a need for restricting foreign direct investment in China's coal mining industry. While foreign direct investment in China's coal mining industry does not appear to be making a statistically significant contribution to productivity of domestic coal mining firms, based on the results presented in this paper, it can be argued that Chinese mining firms that conduct R&D are more likely to be able to compete with highly productive foreign firms both in China and abroad. As China's R&D spending is expected to rise in the future, there is a strong possibility that productivity of domestic coal mining firms will continue to increase. As a result of the increase in productivity, China's mining-related outward FDI is likely to increase in the future.

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Table 1: Correlation of GDP, Coal Production and Coal Imports			
	GDP	Coal Production	Coal Imports
Level			
GDP	1		
Coal Production	0.98	1	
Coal Imports	0.88	0.85	1
Growth Rate			
GDP	1		
Coal Imports	-0.02	0.11	1
Source: Author calculations using data from National Bureau of Statistics			

Table 2: China's Coal Mining Industry Summary Statistics					
Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
labour productivity	19414	4.23	1.17	-1.36	8.42
sales	19413	2.30	0.12	0.83	2.84
profitability	19413	0.09	0.23	-12.19	9.01
market share	19414	0.0005	0.01	0	0.42
firm size	19414	-1.82	1.22	-4.83	5.06
firm age	18652	12.70	12.82	1	128
capital intensity	19414	3.62	1.17	-2.64	8.52
average wage	19414	2.75	0.64	-0.44	5.29
FDI	19414	0.06	0.01	0.00	0.07
Herfindahl	19414	0.01	0.01	0.01	0.22
overall industry concentration	19414	5.97	67.79	0.01	2176.39
ownership	19414	0.45			
drd	19414	0.30			
middle	19414	0.53			
western	19414	0.03			

Note: the labour productivity, sales, size (i.e., number of employees in thousands), age, capital intensity and average wage are in natural logarithm form; *ownership, drd, western,* and *middle* are four dummy variables and their mean is the percentage of observations that take a value of 1.
Source: Industrial Enterprise Data, NBS, 2005-2007

Table 3: Measurement of Imbalance				
	Coal Mining Industry			
	L_1		Mean	
	Before	After	Before	After
overall L_1	0.99	0.85		
year	0.03	0.00	0.05	0.00
region	0.09	0.00	-0.27	0.00
firm size	0.53	0.06	2.39	0.02
age	0.30	0.07	13.10	0.20
capital intensity	0.25	0.05	0.52	0.01
average wage	0.22	0.07	0.21	0.00
ownership	0.25	0.00	-0.25	0.00

Note: "Before" and "After" denote the imbalance before and after the CEM matching respectively

Table 4: Estimation Results for China's Coal Mining Industry								
	productivity		sales		profitability		market share	
Regressors	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error	Estimated Coefficient	Standard Error
firmsize	-0.1320***	0.0186	0.0723***	0.0018	0.0039	0.0041	0.0006***	0.0001
age	-0.0047**	0.0019	-0.0006***	0.0002	-0.0010**	0.0004	0.00003***	0.00001
k	0.3530***	0.0250	0.0293***	0.0025	0.0013	0.0055	0.0004***	0.0001
averagewage	0.5130***	0.0492	0.0332***	0.0049	0.0337***	0.0108	0.0007***	0.0002
ownership	0.2207***	0.0571	0.0209***	0.0057	-0.0026	0.0125	0.0008***	0.0002
western	-0.2925***	0.0694	-0.0417***	0.0069	-0.0390***	0.0152	-0.0003	0.0002
middle	-0.1273**	0.0650	-0.0194***	0.0064	-0.0397***	0.0142	0.0001	0.0002
herfindahl	3.1571	6.1977	0.0819	0.6136	1.5496	1.3553	0.2358***	0.0197
oic	-0.00050	0.0017	-0.000065	0.00017	-0.00004	0.0004	0.000004	0.000005
fdi	-0.3676	4.9582	0.2276	0.4908	0.6450	1.0843	-0.0281***	0.0158
drd	0.2717***	0.0586	0.0312***	0.0058	0.0128	0.0128	0.0003	0.0002
constant	1.3222***	0.4024	2.2351***	0.0398	0.0034	0.0880	-0.0031	0.0013
No. of obs.	1353		1353		1353		1353	
F	54.23		252.19		3.7		60.63	
Adjusted R^2	0.3		0.67		0.02		0.33	
Note: ***, **, and * denote significance at 1, 5, and 10 per cent level respectively								