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The Effect of Energy Structure on Pollution Emissions: The Role of Technological Innovation

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Using a panel data of 30 Chinese provinces from 2000 to 2016, we investigate the linear and nonlinear effects of industrial energy structure on pollution emissions. We find that: (1) technological innovation can alleviate the restraining effect of coal-based energy structure on pollution emissions; and (2) industrial energy consumption significantly increases pollution emissions, while this increase has also occurred in parallel with an increase in the proportion of R&D input.

I. Introduction

China's industry has developed dramatically since 1978. The share of the country's three major industries in GDP shifted from 27.7%, 47.7%, and 24.6%, respectively, in 1978 to 7.7%, 37.8%, and 54.5% in 2020 (NBSC[1], 2021). However, the fast expansion of these industries poses great pressure on energy consumption. Specifically, the share of coal consumption in total energy consumption has fallen from 68.5% in 2000 to 57.7% in 2019; this ratio for the industrial sector remains high, with a value of 79.44%, implying that coal-based energy consumption is the main resource for stimulating China's industrial growth. Unfortunately, total discharge of pollutants currently exceeds the environmental capacity to absorb them (Li et al., 2019).

Economists have contended that technological innovation (*TI*) is an enabler of economic growth. Schumpeter (1912/1934) incorporated *TI* into economic analysis and further stressed that economic growth is an evolutionary process with *TI* as its core. Romer (1990), Grossman & Helpman (1991), and Aghion & Howitt (1992) considered R&D as a form of a firm's decision-making and endogenised the impact of *TI* on economic growth. It is agreed that *TI* is vital for countries worldwide to achieve green development (Shao et al., 2021). Green *TI* is an essential enabler for facilitating green development (Wurlod & Noailly, 2018).

Two opposite viewpoints can be identified regarding the effect of *TI* on sustainable development. *TI*, in particular green technologies, can promote sustainable development (Ghisetti & Quatraro, 2017) by reducing pollutant emissions (PE) (Blum-Kusterer & Hussain, 2001). By developing environmentally-friendly technologies, enterprises can lower energy consumption and limit PEs to ensure cleaner production. Besides, resource recovery technologies can help recycle production wastes, improving energy utilisation efficiency. Green *TI* facilitates a leap for rising economies from the high-pollution phase of nascent development to the "harmonisation" phase of the environmental Kuznets curve. Considering that *TI* has opportunity costs, technology transfer with a low rate could make innovation gains less than its opportunity costs, thereby reducing the intensification degree of economic growth. Still, *TI* may increase energy consumption through the rebound effect (Vélez-Henao et al., 2019). Firms usually neglect environmental costs to maximise their profits (J. Zhang et al., 2018), resulting in the exacerbation of environmental pollution.

It is noteworthy that energy consumption need to be assessed in close conjunction with people's living standards to understand their net affects (Sethi & Dash, 2022). Because various indicators of quality-of-life index are considered to be highly associated with energy consumption (Mazur, 2011), energy consumption plays a crucial role in the determination of the Human Development Index and the level of sustainable development (Van Tran et al., 2019). Energy consumption is demonstrated by Li et al. (2022) to be the main contributor to environmental deterioration. Zhang et al. (2021) assert that coal-based energy structure (*ES*) is the main source of greenhouse emissions.

Against this background, it is interesting to question what the role of *TI* is in the relation between *ES* and *PE*

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1 http://www.stats.gov.cn/.

reduction at the industry level. Specifically, the study explores whether industrial *ES* contributes to *PEs* and how *TI* affects *PEs* through *ES*. The remainder of this paper is structured as follows. Section II designs the methodology. Section III reports the empirical findings, while Section IV makes conclusions.

II. Methodology

Using a panel data of 30 Chinese provinces from 2000 to 2016, we first examine the linear effect of industrial *ES* on *PEs* by implementing a dynamic spatial Durbin model (DSDM). We measure ES as the proportion of industrial coal consumption to industrial energy consumption (*ES1*) and the ratio of industrial energy consumption to business value (*ES2*), and *PE* as sulfur dioxide (SO_2) emission per unit of business value (*SO2Intensity*). The model is as:

$$lny_{it} = \alpha lnX_{it} + \tau lny_{it-1} + \theta wlnX_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where y_{it} denotes the *SO2Intensity*; X_{it} represents the regressors, including total population (*lnpop*), economic growth proxied by per capita gross domestic product (*lnrpgdp*), average assets of firms (*lnaaf*), completed investment in wastewater (*lniwt*), and waste gas treatment (*lnwgt*); α is the direct coefficient of the explanatory variables; θ is the spatial lag coefficient of the explanatory variables; τ is the temporal lag coefficient of the explained variable; μ_i and λ_t denote individual and time-period fixed effects, respectively, while ε_{it} denotes the error term. The indicator w is the spatial weight matrix, which is determined by the product of the geographical distance weight matrix and the diagonal matrix of the proportion of real gross domestic product (Yao et al., 2021).

To better deal with the endogeneity problems between variables, we adopt the dynamic panel threshold model (DPTM). This model also allows us to verify the potential nonlinear relationship between *ES* and *SO2Intensity* under *TI*. The DPTM is specified as:

$$\begin{aligned} lny_{it} = \beta + \alpha_1 lny_{it-1} + \alpha_2 lnSO_2 \cdot I(\gamma_{it} \le \kappa) \\ + \alpha_3 lnSO_2 \cdot I(\gamma_{it} > \kappa) \\ + \sum_{k=1}^{5} \rho_k X_{kit} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (2)$$

where γ_{it} is the threshold variable (*TI*); $I(\cdot)$ represents the indicator function; and κ is the specific threshold value.

The data mainly comes from the China Statistical Yearbook, China Environmental Statistical Yearbook, and the National Bureau of Statistics of China. The monetary variables have been deflated to 2000 constant prices.

III. Findings

As depicted in Fig. 1, most provinces are mainly distributed in the first and third quadrants, indicating that provinces with higher *SO2Intensity* are spatially adjacent. In comparison, provinces with lower *SO2Intensity* tend to be concentrated. The values of global Moran's I are all significantly positive at a 1% significance level, indicating *SO2Intensity* has a positive spatial autocorrelation.

Second, the significance of *SO2Intensity*'s coefficients proves the "accumulation effect" of *PE*. The coefficient of *ES1* in column 2 and its spatial lag term in columns 1 and 2 are positive at a 1% significance level after controlling covariables, suggesting that coal-based *ES* is a significant factor causing *PEs* in local and adjacent areas (W. Zhang et al., 2021). Under the constraint of technological capability, the increase in output requires the massive investment of capital and energy, which is associated with dramatical *PEs* (see columns 4 and 6). Eq. (1) is further extended by adding the interaction term ($ES \times TI$) to verify the moderating effect of *TI*, as reported in columns 3 and 6.[2] Similar to Carrión-Flores & Innes (2010), *TI* significantly contributes to *SO2Intensity*. Polluted environments could negatively affect the emotions of corporate executives, causing them to reduce investment in the technology commercialisation process (Lin et al., 2021).[3] While the collaborative effect between *ES* and *TI* inhibits *SO2Intensity*, the corresponding coefficient in column 6 is statistically significant.

We conduct a robustness test by constructing a new spatial weight matrix using Eq. (3). Table 2 proves the reliability of the benchmark regression. The alternative spatial weight matrix is constructed as follows:

$$w_{ij}^2 = \begin{cases} \frac{1}{d_{ij}} \left(\frac{RGDP}{RGDP}\right)^{\frac{1}{2}} & , i \ne j \\ 0 & , i = j \end{cases} \quad (3)$$

where d_{ij} is the geographical distance of province i and j.

On the one hand, professional talents and resources will be absorbed by developed regions in a shorter period, which is caused by the "polarisation effect", thereby curbing *TI*'s improvement in the adjacent areas. On the other hand, the so-called "trickle-down effect" implies that the local area will feedback surrounding areas through capital outflow and technology overflow, thereby reducing *PEs* in surrounding areas in the long run.

Third, the above analysis shows that *TI* negatively moderates local *SO2Intensity* but has a positive moderating effect in adjacent areas. We infer that the effect of *TI* may not function as a mutational model but as a structural-gradual model. Under different *TI* modes, *ES* may have different effects on *SO2Intensity*. Subsequently, the two-step system generalized method of moments DPTM is performed by treating *TI* as a threshold variable.

2 The variable *TI* is proxied by the ratio of R&D input to gross domestic product.

3 Theoretically, with sufficient funds and stringent environmental regulation, firms actively conduct R&D activities, thus producing "Porter Effect" and stimulating economic growth. However, the crucial reason for the negative coefficients should be dated back to the unstable growth of R&D investment.

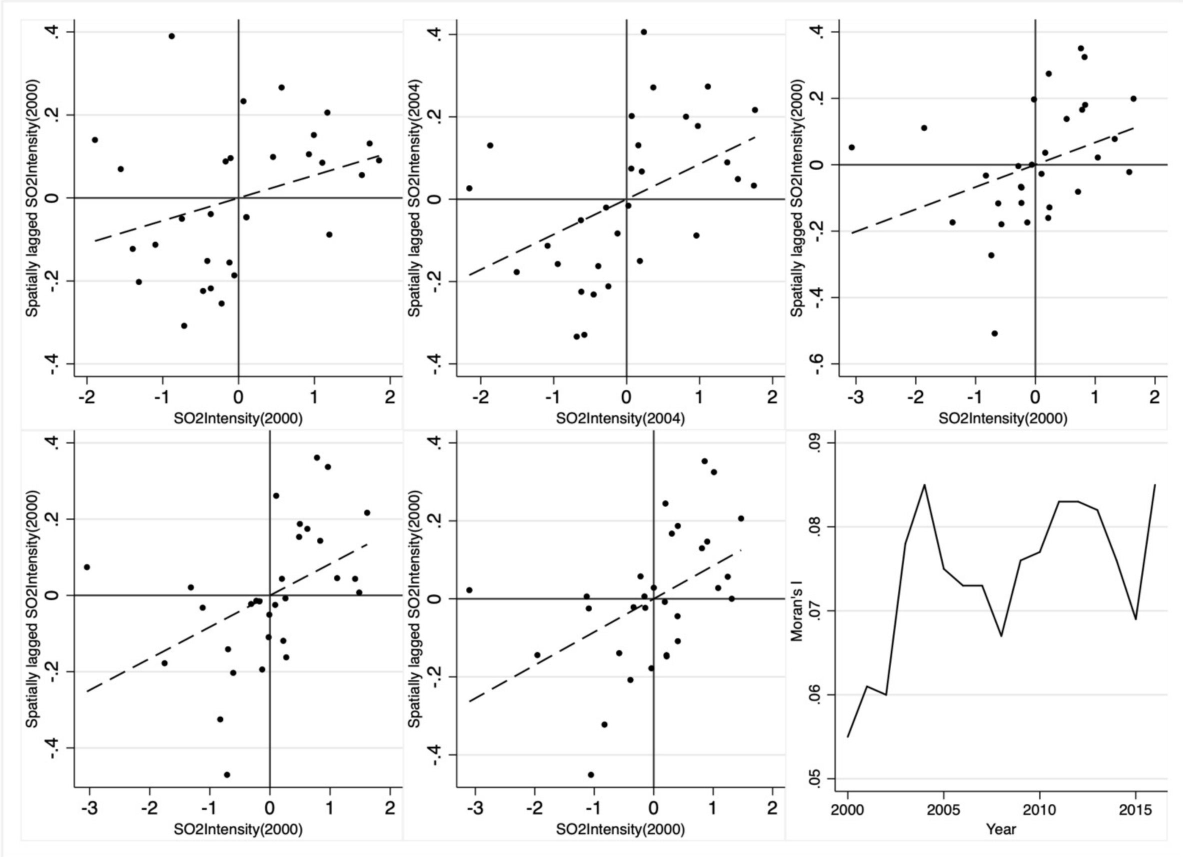

Figure 1. Results of Moran scatterplot and global Moran's I.

According to the Wald statistics, all models exhibit significant threshold effects, indicating that the impact of *ES* on *SO2Intensity* is nonlinear. Specifically, the Sargan test shows no second-order autocorrelation for the random error term; the Hansen test proves the feasibility of the instrumental variables. Thus, the SPTM regression results reported in this paper is credible. Specifically, when *TI* exceeds 2.6300, the positive effect of *ES1* on *SO2Intensity* gradually decreases. The "Porter Effect" will force firms to re-articulate production layout, thereby realising "win-win" situation.

By contrast, when *TI* is higher than 2.5290, the effect of *ES2* on *SO2Intensity* increases monotonically. For emission mitigations and energy conservations, tradeoffs between the economic and environmental goals should be addressed by balancing production adjustment and ecological investment. However, technological enhancements significantly impact ecology but require a large investment in money and time (Xu et al., 2017). Compared to the eastern region, China's central and western regions lagged far behind regarding economic strength and *TI* levels. Thus, the increase in total energy consumption is expected to increase pollution emissions in a shorter period because of restriction of *TI* and other growth-improving activities.

IV. Conclusions

We investigate the industrial *ES*–*PE* nexus using the DSDM and DPTM models. Our findings show that *ES* significantly promotes PE. TI's improvement can alleviate the restraining effect of coal-based *ES* on *PE*. Similarly, industrial energy consumption also significantly increases *PE*, but this increase occurs in parallel with an increase in the proportion of R&D input.

Our study has some important implications. First, government should firmly carry out supply-side structural reform to force the transformation and adjustment of industries by attracting high-tech industries. Second, as the spatial spillover effect of TI has not yet been established, thus, a sound regional cooperation mechanism should be constructed to better play the spatial spillover effect of TI. Third, sufficient funds from financial institutions and local governments are also required. This is because the innovative capability of the eastern region is better than the central and western regions. In other words, the collaborative effect between ES and TI may exist significant regional heterogeneity, which also provides a crucial information for us further exploration.

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Table 1. Results of benchmark model and moderating effects

	(1)	(2)	(3)	(4)	(5)	(6)
L.lSO2Intensity	0.98627***	1.08794***	0.93657***	1.00252***	1.04655***	1.03092***
	(0.009)	(0.012)	(0.026)	(0.009)	(0.012)	(0.012)
lnTI			-0.04203***			0.25508***
			(0.009)			(0.072)
lnECS1	0.02678	0.12826***	0.26173*			
	(0.019)	(0.024)	(0.137)			
lnECS1×lnTI			-0.02937			
			(0.031)			
lnECS2				0.01322	0.09012***	0.06666***
				(0.012)	(0.015)	(0.017)
lnECS2×lnTI						-0.03973***
						(0.010)
w∗lnECS1	3.73411***	3.47880***	0.87033***			
	(0.136)	(0.138)	(0.167)			
w∗(lnECS1×lnTI)			0.01058			
			(0.020)			
w∗lnECS2				0.59460***	0.61541***	1.22485***
				(0.079)	(0.080)	(0.090)
w∗(lnECS2×lnTI)						0.17680***
						(0.012)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
ρ	0.25301***	0.09968**	0.49091***	0.17074***	0.10400*	0.19858***
	(0.043)	(0.048)	(0.036)	(0.061)	(0.062)	(0.064)
Sigma2_e	0.01482***	0.01410***	0.01616***	0.01419***	0.01396***	0.01360***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obs.	480	480	480	480	480	480
R-squared	0.92917	0.92222	0.71029	0.94856	0.93289	0.89861
L-ratio	348.71161	359.34358	319.93660	357.38154	361.07513	367.35291

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is logarithm *SO2Intensity*.

Table 2. Robustness test

	(1)	(2)	(3)	(4)
L.lSO2Intensity	1.09328***	1.45860***	1.03123***	1.02097***
	(0.012)	(0.012)	(0.012)	(0.012)
lnTI		0.44771***		0.36933***
		(0.061)		(0.072)
lnECS1	0.12682***	-0.23300***		
	(0.023)	(0.024)		
lnECS1×lnTI		-0.11778***		
		(0.016)		
lnECS2			0.10757***	0.05069***
			(0.015)	(0.017)
lnECS2×lnTI				-0.05818***
				(0.010)
w∗lnECS1	2.16397***	2.30389***		
	(0.117)	(0.119)		
w∗(lnECS1×lnTI)		0.37705***		
		(0.020)		
w∗lnECS2			0.69615***	1.10115***
			(0.071)	(0.074)
w∗(lnECS2×lnTI)				0.15958***
				(0.011)
Control variables	Yes	Yes	Yes	Yes
ρ	0.27706***	0.24350***	0.04682	0.36559***
	(0.045)	(0.053)	(0.046)	(0.056)
Sigma2_e	0.01395***	0.01370***	0.01371***	0.01347***
	(0.001)	(0.001)	(0.001)	(0.001)
Obs.	480	480	480	480
R-squared	0.94871	0.89235	0.91574	0.87181
L-ratio	359.39887	366.13709	360.14525	366.04822

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is logarithm *SO2Intensity*.

Table 3. Results of DPTM.

	(1)	(2)
$\widehat{\kappa}$	2.63000	2.52590
	[0.3401, 2.9642]	[0.3401, 2.9642]
L.lSO2Intensity	0.77474***	0.86899***
	(0.030)	(0.031)
$\widehat{\alpha}_2$	0.44709***	0.18942***
	(0.061)	(0.026)
$\widehat{\alpha}_3$	0.38987***	0.35955***
	(0.06978)	(0.063)
_cons	1.34272***	-0.10231
	(0.492)	(0.523)
AR (2)	1.00	1.26
Hansen_statistics	29.17	28.46
Wald_statistics	26302.95***	12688.33***

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All control variables have been controlled. The dependent variable is logarithm *SO2Intensity*.

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