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Threshold Effect of Environmental Regulation on Eco-Friendly Productivity: Empirical Evidence From China

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This paper identifies the existence of a significant nonlinear relationship between environmental regulation (*ER*) and eco-friendly efficiency (*EFE*) adopting the panel smooth transition regression model. It is interesting to find that *ER* has temporarily inhibited *EFE* growth in China. An initial downward trend is reversed and shows upward improvement from a distinct point, creating a V-shaped trend.

I. Introduction

China's President Xi, in the 19th National People's Congress of the Communist Party of China, announced that China had turned to a stage of high-quality development (HQD). That is, HQD had become a crucial guiding ideology in the future economic development and social construction in China. Therefore, how to achieve the old and new kinetic energy transformation and promote HQD is a heated topic in current economic studies. However, the negative externalities imposed by the traditional extensive economic development pattern have triggered imbalances such as environmental deterioration in China's socioeconomic development (Hong et al., 2022). It is undeniable that energy plays a crucial role in improving people's wellbeing (Li & Lin, 2017). To some extent, China's rapid economic growth was driven by massive energy consumption (Zhu et al., 2019). Specifically, China's total energy consumption has increased from 5.714 million tons of standard coal in 1978 to 4.98 billion tons of standard coal in 2020 (National Bureau of Statistics of China, 2021).¹ Meanwhile, China is also the world's largest energy consumer and CO₂ emitter (Wu, Ren, et al., 2020). To this end, facing severe environmental issues and energy scarcity, China must adapt its economic development model and introduce feasible policies that are in line with inclusive development.

Environmental governance can be considered as an effective instrument in enhancing energy efficiency and addressing negative externalities of environmental pollution (Costantini & Crespi, 2008; Sun et al., 2019). China has successively enacted several energy saving and emission alleviation policies such as The Energy Development Strategic Action Plan. In the meantime, the share of fiscal expen-

diture for energy conservation and environmental protection has dramatically increased from 2% in 2007 to 4% in 2020. Additionally, China also marked great achievements in environmental policy innovations from the institutional perspective, highlighting the re-articulation of the existing environmental regulation (*ER*) system, the execution of the local government's ecological duty and social inclusive development (Li & Lin, 2019). The essence of *ER* lies in authorities' allocation of environmental protection affairs among different levels of government, namely, environmental decentralization.

Empirical findings have suggested that *ER* can affect eco-friendly efficiency (*EFE*) through labour productivity improvement (Song et al., 2022) or technological progress (Song et al., 2022), which explicitly implies nonlinearity between *ER* and *EFE*. Adopting China's 30 provinces from 2005 to 2016, we validate the potential non-linear effect of *ER* on *EFE* by implementing the Panel Smooth Transition Regression (PSTR) model.

The remainder of this paper is organised as follows: Section II describes the methodology. Section III reports the empirical findings. Section IV concludes this study.

II. Methodology

First, *EFE* is defined as the proportion of theoretical minimum factor inputs to the actual input levels when the bad output is minimised under a bundle of good outputs. Following Zhang et al. (2015) and Li & Lin (2017), we take bad output into full account to measure *EFE*, adopting Super-SBM model. Specifically, capital, labour, and total energy consumption are selected as input factors. The expected output is GDP. Wastewater discharge, solid waste

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¹ See <http://www.stats.gov.cn/>.

generation and exhaust gas emission are treated as bad outputs.

Second, three indicators (namely, wastewater compliance rate, SO₂ removal rate and industrial solid waste comprehensive utilization rate) are applied to establish a performance-based ER index system (Wu, Xu, et al., 2020). Specifically, the adjusted coefficient is:

$$\mathcal{R}_{ij} = \frac{\mathcal{R}_{ij}}{\sum_i \mathcal{R}_{ij}} / \frac{RGDP_i}{\sum_i RGDP_i} \quad (1)$$

where $\mathcal{R}_{ij}$ denotes the discharge of the pollutant i of the province, which is normalised using $\mathcal{R}'_{ij} = \frac{[\mathcal{R}_{ij} - \min(\mathcal{R}_{ij})]}{\max(\mathcal{R}_{ij}) - \min(\mathcal{R}_{ij})}$ ($\min(\mathcal{R}_{ij})$ and $\max(\mathcal{R}_{ij})$ are minimum and maximum values of $\mathcal{R}_{ij}$); $RGDP_i$ represents the real GDP in province i . If the emission of pollutant i in the i th province is high, then the same pollution rate indicates stronger ER , and the weight assigned would be higher. Using the normalised values and $\mathcal{R}_{ij}$, ER is calculated as follows:

$$ER = \sum_{j=1}^3 \frac{1}{3} \mathcal{R}'_{ij} * \mathcal{R}_{ij} \quad (2)$$

We improve the model developed by Nasreen & Anwar (2014) by incorporating other macro factors.

$$EFE_{it} = \alpha_i ER_{it} + \alpha'_{it} ER_{it} \cdot I(T_{it-1}; \gamma, \vartheta) + \vartheta_j x_{j,it} + \vartheta'_j x_{j,it} \cdot I(T_{it-1}; \gamma, \vartheta) + \mu_i + \varepsilon_{it} \quad (3)$$

where μ_i denotes individual fixed effect; ε_{it} is the error term; $I(T_{it-1}; \gamma, \vartheta)$ represents a transition function of the threshold indicator T_{it-1} , which is continuous and bounded between 0 and 1 (see Ullah et al., 2021). $I(T_{it-1}; \gamma, \vartheta) = 0$ suggests a linear relationship (Regime 1), while $I(T_{it-1}; \gamma, \vartheta) = 1$ indicates a non-linear relationship (Regime 2). Exogenous variables or a combination of lagged endogenous variables can be treated as a threshold indicator (Lee & Chiu, 2011, 2012). The lagged explanatory variable is treated as a threshold indicator T_{it-1} . $x_{j,it}$ denotes the selected control variables, namely, foreign direct investment (fdi), infrastructure (if), economic growth ($pgdp$), industrial structure (is), and R&D input (ri). All variables have been transformed into the natural logarithms.

Following Colletaz et al. (2006), we consider the following transition function of logistic specification:

$$I(T_{it-1}; \gamma, \vartheta) = \left[1 + \exp \left(-\gamma \prod_{j=1}^m (T_{it-1} - \vartheta_j) \right) \right]^{-1}, \quad (4)$$

$$\gamma > 0, \vartheta_1 \leq \dots \leq \vartheta_m$$

where $\vartheta = (\vartheta_1, \dots, \vartheta_m)'$ represents an m -dimensional vector of location parameters; coefficient γ captures the smoothness of transition. The model collapses into linear regression model with fixed effect, assuming $\gamma > 0, \vartheta_1 \leq \dots \leq \vartheta_m$. Thus, PSTR model with multiple regimes is specified as

$$EFE_{it} = \alpha_i ER_{it} + \sum_{i=1}^q \alpha'_{it} ER_{it} \cdot I_j(T_{it-1}^j; \gamma_j, \vartheta_j) + \vartheta_j x_{j,it} + \sum_{i=1}^q \vartheta'_{ij} x_{j,it} \cdot I_j(T_{it-1}^j; \gamma_j, \vartheta_j) + \mu_i + \varepsilon_{it} \quad (5)$$

Transition functions $I_j(T_{it-1}^j; \gamma_j, \vartheta_j)$, $j = 1, \dots, q$ depend on the slope coefficients γ_j and location coefficients ϑ_j . If $q = 1$, $T_{it-1}^j = T_{it-1}$, and $\gamma_j \rightarrow \infty$ for all j , $I_j(T_{it-1}^j; \gamma_j, \vartheta_j)$ is assumed as an indicator function. Equation (5) is a panel transition regression model with $q + 1$ regimes. Thus, ER 's elasticity coefficient (EC) on EEF for province i at year t is given as:

$$e_{it}^{ER} = \frac{\partial EFE_{it}}{\partial ER_{it}} = \alpha_i + \sum_{j=1}^q \alpha'_{it} I_j(T_{it-1}^j; \gamma_j, \vartheta_j) \quad (6)$$

where e_{it}^{ER} is the estimated EEF improvement (or degeneration) in terms of ER . e_{it}^{ER} varies both over year and across provinces. Parameters α_i and α'_{it} regulate the ECs of linear and nonlinear models, respectively.

The PSTR model proposed by Gonzalez et al. (2004) allows for a small number of extreme regimes linked to the extreme value of a transition function. Also, it allows for a continuum: each one is characterised by a different value of the transition function. In our context, the PSTR allows cross-provincial heterogeneity and time instability of the elasticities without configuration of ex-ante classification over individuals. It is therefore suitable to adopt the PSTR model to capture the possible nonlinearity between ER and EFE .

All monetary indicators have been converted into 2005 constant price. The data is mainly collected from China Environmental Statistics Yearbook, China Energy Statistics Yearbook, China Science and Technology Yearbook, and National Bureau of Statistics of China.

III. Findings

First, we check whether ER has a non-linear effect on EFE (Colletaz et al., 2006). Results reported in Panel A of Table 1 rejects the null hypothesis at a 1% significance level, highlighting that ER has a nonlinear effect on EFE .

Second, the remaining non-linearity test² is applied to verify whether the model is adequately estimated and then determines the number of transition functions. Specifically, the model is considered as reasonable if the null hypothesis is supported. Conversely, if the null hypothesis is rejected, then the model may contain multiple transition functions. Panel B of Table 2 displays that Equation (5) has been iteratively examined and the null hypothesis has been accepted until $H_0: q = 2$, implying that Equation (5) converges to three-regime PSTR model.

Third, Table 2 displays that there are two structural breakpoints for the ER - EFE nexus. Specifically, a dramatic change between Regimes 1 and 2, because of the high

2 The remaining non-linearity test is carried out with $q = 2$ alternative hypotheses.

Table 1. Results of linearity and remaining tests

Panel A: Linearity test results.		
LM		122.242***
LMF		8.912***
LRT		149.346***
Panel B: Remaining nonlinearity test results.		
$H_0 : r = 1 \text{ v. } H_1 : r = 2$		
LM		40.986***
LMF		6.681***
LRT		43.513***
$H_0 : r = 2 \text{ v. } H_1 : r = 3$		
LM		19.576***
LMF		2.933***
LRT		20.128***

This table reports the linearity test results and remaining nonlinearity test results in Panels A and B respectively. *** denotes statistical significance at 1% level. The null hypothesis H_0 : the model is linear; the alternative hypothesis H_1 : the model is nonlinear. The dependent variable is logarithm of *EFE*.

γ value. At this point, the transition function tends to be an indicator function. The transition from Regime 2 to 3 shows a sharp decline, with a difference of 3.2428. The regression results also show that if *ER* is lower than -1.2409, *EC* is -1.1587 and such an effect is statistically significant. If *ER* is more than -1.2409 but less than -0.1124, *EC* is -1.0713, while if *ER* exceeds -0.1124, *EC* converges to -1.0827.

The above estimated results imply that stringent *ER* could inhibit *EFE* enhancement, while the influential magnitude has exhibited an “V-shaped” trend. More specifically, even before *ER* reaches its turning point, an enhancement in *ER* will inhibit *EFE* improvement. The inhibitory effect shows a decreasing trend after strengthening *ER* by a certain degree. Unfortunately, further improvement in *ER* will once again curb *EFE* in the long run. This should be attributed to the following explanations. On the one hand, when *ER* degree is low, payment costs of environmental deterioration is triggered by *ER* account for a small share of firms’ total cost. Thus, firms lack the motivation to conduct R&D activities to achieve a “win-win” situation of energy conservation and pollution reduction (Saidi & Hammami, 2015). Besides, the compliance cost of *ER* will reduce firm’s profits. It would be virtually impossible to encourage firms to carry out technological research, and this would hinder *EFE* in the short term (Esso & Keho, 2016). As a result, firms have to re-structure their production layout and update their production techniques, and ultimately improve *EFE* (Peuckert, 2014). On the other hand, China Environmental Protection Tax Law pays less attention to consumption-based environmental responsibility. According to Xue et al. (2022), the configuration of China’s current tax rates is not optimal, which mainly reflects that inter-provincial trade activities lead to cross-border pollution emission transfer that brings a burden on provinces with low tax rates. Consequently, pollution emissions generated from the developed and coastal provinces will be transferred to the developing and interior provinces.

Moreover, tax revenue obtained from related policies will be fed back to the economy to maintain government revenue. For example, revenues from specific taxes will be applied to compensate for the revenue loss from the reduction of corporate and personal income taxes and offer lump-sum transfers to those low-income groups (Yamazaki, 2022). Therefore, in the long-term, the willingness of firms to pursue technological innovation and emission reduction may decrease, thereby hindering *EFE*.

IV. Conclusion

Our findings reflect the existence of a strongly nonlinear relationship between *ER* and *EFE*. *ER* has inhibited *EFE* in China. The inhibitory effect first decreases and shows an upward trend with further improvement in *ER* and, thus, forming a “V-shaped” trend. Thus, we recommend that: (1) China should carefully design scientific and stringent environmental policies that are in line with regional and national realities. This would trigger the “Porter Effect” and strengthen the independent innovative capability of firms, thereby ultimately improving *EFE*; (2) China streamlines administration in *ER* and give full play to the decisive role of the market in resource allocation; (3) Relevant authorities should actively refine the China’s negative list for market access.

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Table 2. Empirical results

	α	α'	
<i>lnER</i>	-1.1587*** (-3.1360)	0.0874*** (3.6995)	-0.0114 (-1.0240)
<i>lnfdi</i>	-0.0648** (-2.0842)	0.0920*** (3.4247)	-0.0277 (-0.9308)
<i>Lnif</i>	0.1584*** (5.3396)	-0.1441*** (-5.1787)	-0.0374** (-1.8996)
<i>lnpgdp</i>	0.8301*** (6.1128)	-0.4484*** (-3.6392)	-0.2883 (-3.5185)
<i>lnis</i>	0.0769*** (2.5336)	-0.0700** (-2.3021)	0.0292 (1.0137)
<i>lnri</i>	-0.0932*** (-2.345)	0.0232 (0.8271)	-0.0792*** (-4.0321)
ϑ	-1.2409; -0.1124		
γ	12.6729; 9.4301		

This table reports the estimated results for variables as well as results of location and slope parameters. α and α' represent the linear and nonlinear coefficients, respectively. ϑ and γ regulate location parameter and slope parameter, respectively. Following Ben Lahouel et al. (2021), F test is 0.790 (p-value=0.3813). Thus, we conclude there is no serial autocorrelation. *t*-statistics are reported in parentheses. ** and *** denotes statistical significance at 5% and 1% level, respectively.



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