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Stringency of Environmental Regulation and Eco-innovation: Evidence from the eleventh Five-Year Plan and Green Patents

Effie Kesidou

Economics Division, Leeds University Business School, University of Leeds, Leeds, UK

Lichao Wu

Department of International Economics and Trade, School of Economics, Xiamen University, Xiamen, China

Abstract:

Using the variation in pollution reduction targets across provinces and time variations (before and after the eleventh Five-Year Plan), we examine the impact of stricter environmental regulation upon the production of green patents by firms in China. We find that Chinese manufacturing firms, located in provinces with stricter pollution targets, produced a higher volume and intensity of green patents. Our results suggest that stricter environmental regulatory frameworks in emerging economies are not only combating pollution, but also shifting the innovation activities of manufacturing firms towards building a stock of knowledge in environmental protection. This process, undoubtedly, has the potential to generate disruptive eco-innovations.

JEL classification: O32, Q55, Q53.

Keywords: Environmental regulation; Eco-innovation; Green patents; Difference-in-differences

1. Introduction

25 years ago, Porter and van der Linde (1995) proposed that environmental regulation can reduce pollution by boosting the type of innovation that may compensate, to some extent, compliance costs. The Porter Hypothesis is still contentious in economics as some of its premises are still unclear today. Among these are, firstly, whether environmental regulations drive various types of innovation; secondly, which type of environmental regulation is more appropriate (flexible policies versus technology standards); and finally, whether regulation-induced innovations offset the costs of complying with regulations, which in turn, increases firm's profitability. Research in environmental economics suggests that flexible policies [1] are more cost-effective in inducing the adoption and development of green technologies compared to policies based on technology standards[2] (Orr, 1976; Milliman and Prince, 1989; Jung, et al.,1994). Recent studies show that the stringency[3] of environmental regulation is more significant in inducing eco-innovations rather than the choice of flexible versus technology standards. Strict regulations enable green technologies to compete with similar incumbent technologies (Grubb et al., 2014).

Whilst the Porter Hypothesis has been tested in advanced economies (Kesidou and Demirel, 2012; Brunnermeier and Cohen, 2003), it still remains unclear whether it holds for emerging economies as well. Lanjouw and Mody (1996) questioned whether strict regulation in emerging economies would trigger domestic investments on pollution control technologies or green patenting. They argued that it could equally lead to importing green technologies from advanced economies and reinforcing foreign patenting. We contribute to this literature by empirically testing, for the first time, the causal impact of stricter environmental regulation upon the generation of eco-innovations in manufacturing firms in China.

Building theoretically on the economics of innovation and on our own empirical testing, we contend that besides environmental externalities, a second market failure exists in the case of eco-innovation, which results from the production of knowledge; i.e. spillovers in knowledge (Grilliches, 1994; Jaffe et al., 2005). This occurs because knowledge has attributes of a public good, thus, firms cannot fully appropriate the returns on their investments in knowledge, which leads to underinvestment in research and development (R&D). We, therefore, argue that environmental regulations address this market failure by encouraging firms to invest on green R&D, which in turn, stimulates domestic green patenting.

2. Data and Empirical Methodology

2.1. Data

We analyse a unique panel dataset, which we assembled by merging data from different sources: First, the data on pollution reduction SO_2 emission targets for 31 provinces in China was collected from a document titled '*Reply to Pollution Control Plan During the Eleventh Five-Year Plan*', issued by the China State Council in 2006. This allows us to identify variation across provinces before-and-after the implementation of the environmental policy. Second, to address endogeneity that could arise from provincial SO_2 emission targets, we follow Shi and Xu (2018) to use the ventilation coefficient as an instrumental variable (IV). The ventilation coefficient is based on the product of wind speed and the mixing height for each province. We sourced this information from the European Center for Medium-Term Weather Forecasting ERA-interim dataset[4]. Next, we matched the ERA-interim dataset with the capital city of each province by its latitude and longitude.

Third, the data on green patents granted to all firms was collected from the China National Intellectual Property Administration (CNIPA)[5]. Green patents refer to those IPC classifications, whereby the inventions, utility models, and design patents have a green technology as the main body of the invention. To identify green patents, we use a detailed patent search strategy developed by the OECD (Haščič and Migotto 2015), combined with the "IPC Green Inventory" provided by the World Intellectual Property Organization[6]. Fourth, the industrial survey firm-level data was sourced from the National Bureau of Statistics (NBS). NBS[7] covers all Chinese manufacturing firms with an annual turnover of more than RMB 5 million during the period 2002-2009.

2.2. Methods

Combining the variation in pollution reduction targets across provinces and the time variations (before and after the start of the eleventh Five-Year Plan), we estimate the impact of stringency of environmental regulations on firm eco-innovation using a difference-in-differences (DID) strategy. The following regression is estimated:

$$Eco\text{-}innovation_{ipt} = \alpha * Target_p * Post_t + \beta X + \mu_d + \delta_p + T_t + \varepsilon_{ipt} \qquad (Equ.\ 1)$$

Where $Eco\text{-}innovation_{ipt}$ is measured in two ways for robustness: (i) total number of green patents granted to firm *i* in province *p* and year *t (Ecoinno)* and (ii) share of green patents as a percentage of total patents granted to firm *i* in province *p* and year *t (Ecoinnop).* $Target_p$ measures the pollution reduction targets (i.e. SO_2 emission) set by the Five-Year Plan for province *p.* $Post_t$ is a time dummy variable equal to 0 for 2002-2005, and 1 for 2006-2009. X is a vector of control variables. Specifically, we control for firm-level effects using size and age of the firms (*size, age*), R&D (*rad*), profitability (*profit*), foreign ownership dummy (*FOE*), export propensity (*exp*). μ_d is industry-fixed-effects, δ_p is province-fixed-effects, T_t is year-fixed-effects, ε_{ipt} is error term.

We adjust all variables with logarithmic transformation as follows ln(x +1). The observations of 0 do not pose a serious issue of concern as we employ the DID method. The key notion of this method is that if the treated and the nontreated groups are exposed to the same exogenous time trends, then an estimate of the "effect" of the treatment during the pre-treatment period (when we know that the treatment has had no effect) is used to eradicate the effect of confounding factors when comparing post-treatment outcomes of treated and nontreated groups. Finally, there is a time-lag of 18 months between the filing and the publishing of granted patent applications. Given this, we lagged all the explanatory variables by two years.

Due to the potential endogeneity of the *Target* variable, we adopt an Instrumental Variable (IV) approach. We use the *Ventilation* coefficient as the instrument for the stringency of environmental regulation (i.e. *Target*). According to the Box model, two variables determine pollution dispersion. One is wind speed, as a faster wind speed helps the horizontal dispersion of pollution, and the second is mixing height, which influences the vertical dispersion of pollution. The ventilation coefficient is the product of wind speed and mixing height. Higher ventilation coefficient values mean faster dispersion of pollution, leading to a lower policy intensity in our context.

We examine the robustness of the empirical analysis by using an alternative measure of regulation stringency (based on provinces emission levels), by considering firm heterogeneity (based on R&D intensity), and by controlling for industry heterogeneity (based on industry's technology distance from technology frontier and industry's pollution intensity).

Variables definition, measurements, and summary statistics are provided in Table 1. Figure 1 depicts the distribution of pollution reduction *Targets* across the 31 provinces in China, which vary from 0 to more than 25 per cent with a mean and standard deviation of 9.645 per cent and 6.808 per cent, respectively.

[Table 1]

[Figure 1]

3. Empirical Results

The results of the DID regression are presented in Table 2. Columns (1) and (2) show the results when we use the total number of green patents granted to firm *i (Ecoinno)* as the outcome variable whilst columns (3) and (4) show results when we use the share of green patents as a percentage of total patents granted to firm *i (Ecoinnop)* as the outcome variable. For brevity, only the coefficient of *Target*Post* is presented. The coefficients 0.0008 (column 1), 0.0011 (column 2), 0.0283 (column 3), and 0.0314 (column 4), are all statistically significant at the 1% level.

[Table 2]

We proceed with IV estimation to address potential bias arising from *Target*. Specifically, we use the ventilation coefficient as the instrument for pollution reduction targets for each province. Estimation results are shown in Table 3. Columns (1) and (2) report the first-stage results. The ventilation coefficient is a very strong predictor for pollution reduction targets with F-value of 1.35 and 1.35, respectively. The second-stage results are shown in columns (3) and (4). The results are consistent with the ones presented in Table 2 indicating that the eleventh Five-Year Plan drives firm eco-innovation, with the coefficient of the volume of green patents as 0.0013 (column 3) and of the intensity of green patents as 0.0426 (column 4), respectively.

[Table 3]

Furthermore, we examine the robustness of the results by employing an alternative measure of regulation stringency other than *Target* i.e. targeted pollution reduction SO_2 emissions. The precision of this measurement might be questioned, as even a small percentage could represent a large burden for provinces with heavy pollution. *Target II* is measured by the amount of expected pollution reduction times the percentage of emission levels in 2005 over GDP in 2005 [to account for variation in economy size amongst provinces]. We re-estimate regression equation (1) using *Target II*Post* as an alternative measure of regulation stringency. The results shown in Table 4 remain robust.

[Table 4]

Our results might be biased due to firm heterogeneity arising from different R&D intensities amongst firms. We conduct a sensitivity analysis by including a dummy variable (*rd*), which takes the value of 1 if the R&D intensity of the firm is above the average industry level, and otherwise equals to 0. We re-estimate equation (1) using *Target*Post*rd*. The results shown in Table 5 remain robust.

[Table 5]

Finally, we examine whether our results remain robust when considering variation arising from industry heterogeneity (based on industry's distance from technology frontier and on industry's pollution intensity). An industry's distance from the technology frontier (*IDF*) is a determinant of firms' innovation. $IDF_i = \frac{LP_i^{chn}}{LP_i^{us}}$ is measured as the average labour productivity of Chinese manufacturing industries over the average labour productivity of US manufacturing industries. The larger the *IDF* value, the closer to the international technology frontier. An industry's pollution intensity (*indpollu*) is a determinant of eco-innovation. Industry pollution intensity is a binary variable which takes the value of 1 if a firm belongs to a high pollution intensity industry, otherwise 0. The results shown in Tables 6 and 7 remain robust.

[Tables 6, 7]

4. Conclusions

This study compiles a unique panel dataset and uses the variation in pollution reduction targets across provinces and time variations to examine the impact of regulation stringency upon the generation of green patents by manufacturing firms in China. We find that firms, located in provinces with stricter pollution targets, produced a higher volume and intensity of green patents. Our results, which are based on alternative measures of regulation stringency and to possible bias arising from firm and/or industry heterogeneity, are robust. Our findings demonstrate that environmental regulations have the potential to drive eco-innovation in China, by creating a market for green technologies.

Our analysis provides insights into the Porter Hypothesis, adding some important policy implications for emerging economies. Our results reveal that strict regulation triggers green patenting, rather than solely the diffusion of foreign imported pollution control technologies. Policy makers drawing stricter environmental regulatory frameworks in emerging economies are not only combating pollution, but also shifting the innovation activities of manufacturing firms towards building a stock of knowledge in environmental protection. This process, undoubtedly, has great potential to generate disruptive eco-innovations.

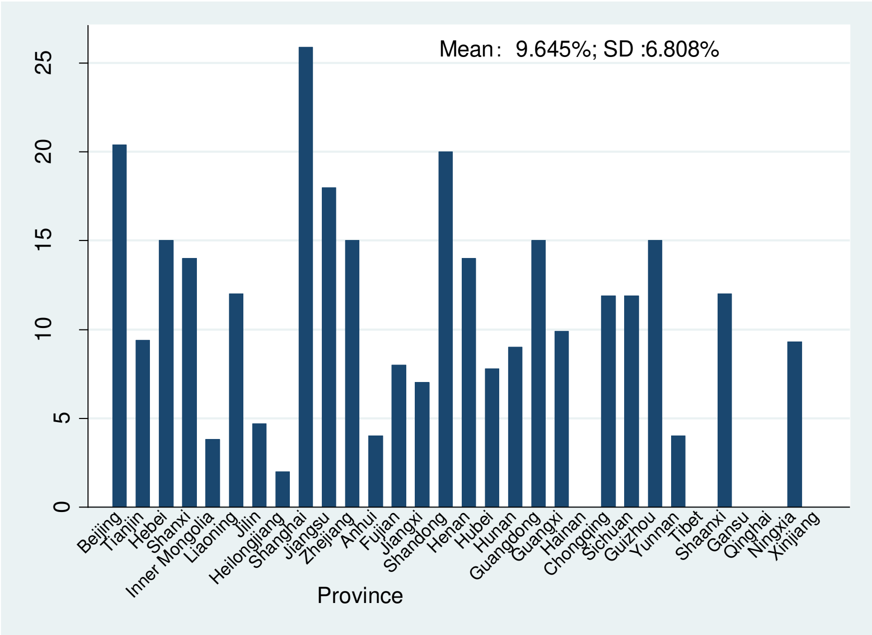
A limitation of this paper is that geographic spillovers might underestimate the results of the DID method and the impact of environmental policy. This is because the stringency of environmental regulation in technological intensive provinces might exert a “direct” effect on firms’ eco-innovation in the same province, and an “indirect” or spillover effect upon firms in closely located provinces. The latter might invest on eco-innovations so as to provide complementary technologies to firms in the strict regulated provinces. Inter-industry spillovers might also be present. For example, when Grover (2017) examined inter-industry spillovers in the US, he found that the effect of pollution abatement R&D that spills over from another industry to a focal industry, causes the focal industry to decrease its environmental R&D investment. Future research should incorporate spillovers into the modelling of eco-innovation as green patenting is not only driven by regulatory stringency or own-R&D, it can also be generated through regional or technological spillovers.

Tables and Figures

Table 1. Variable definition and summary statistics

Index code	Variables	Definition	Obs	Mean	Std.Dev.
Ecoinno	Eco-innovation volume (firm-level)	Green patents granted for each firm (take logarithm)	1,554,464	0.014	0.145
Ecoinnop	Eco-innovation intensity (firm-level)	Green patents granted for each firm scaled by total patents	1,554,464	0.003	0.049
age	Firm age (firm-level)	Firm age (take logarithm)	1,553,981	1.968	0.775
size	Firm size (firm-level)	Firm size (measured by total assets, take logarithm)	1,554,448	9.829	1.429
profit	Profitability (firm-level)	Total profit/Total assets	1,554,450	0.134	6.344
rad	Research and development (firm-level)	R&D (take logarithm)	621,682	0.596	1.881
FOE	Foreign ownership dummy (firm-level)	Foreign-invested enterprises (dummy variable)	1,554,464	0.199	0.399
exp	Export propensity (firm-level)	Export propensity (dummy variable)	1,554,464	0.267	0.442
ac	Ventilation coefficient (city-level)	Ventilation coefficient	3,990	1643.474	501.947

Figure 1. Distribution of Pollution Reduction Targets



Notes: The province names in the x-axis are sorted by their codes assigned by National Bureau of Statistics.

Source: Pollution targets are taken from the document "Reply to Pollution Control Plan During the Eleventh Five-Year Plan," issued by the China State Council.

Table 2. DID estimates: Impact of environmental regulations upon firm eco-innovation

Dependent Variable:	*Ecoinno*		*Ecoinnop*	
	(1)	(2)	(3)	(4)
*Target*Post*	0.0008***	0.0011***	0.0283***	0.0314***
	(0.0001)	(0.0002)	(0.0052)	(0.0096)
Control variables		Yes		Yes
Industry FE		Yes		Yes
Province FE		Yes		Yes
Year FE		Yes		Yes
Observations	1,551,808	621,217	1,551,808	621,217

Notes: Standard errors in parentheses. ***p<1%; **P<5%; *p< 10%.

Table 3. IV estimates: Impact of environmental regulations upon firm eco-innovation

Dependent Variable:	*Target*Post*		*Ecoinno*	*Ecoinnop*
	(1)	(2)	(3)	(4)
	First Stage	First Stage	Second Stage	Second Stage
*Ln(Ventilation)*Post*	0.1101***	0.1101***		
	(0.0001)	(0.0006)		
*Target*Post*			0.0013***	0.0426***
*(Ln(Ventilation)*Post as IV)*			(0.0002)	(0.0109)
Control variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	610,947	610,947	610,947	610,947

Notes: Standard errors in parentheses. ***p<1%; **P<5%; *p< 10%.

Table 4. Robustness analysis: Alternative measure of regulation stringency

Dependent Variable:	*Target II*Post*		*Ecoinno*	*Ecoinnop*
	(1)	(2)	(3)	(4)
	First Stage	First Stage	Second Stage	Second Stage
*Ln(Ventilation)*Post*	0.1113***	0.1113***		
	(0.0001)	(0.0001)		
*TargetII*Post*			0.0013***	0.0421***
*(Ln(Ventilation)*Post as IV)*			(0.0002)	(0.0108)
Control variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	610,947	610,947	610,947	610,947

Notes: Standard errors in parentheses. ***p<1%; **P<5%; *p< 10%.

Table 5. Robustness analysis: Testing for firm heterogeneity (R&D intensity)

Dependent Variable:	*Target*Post*comrad*		*Ecoinno*	*Ecoinnop*
	(1)	(2)	(3)	(4)
	First Stage	First Stage	Second Stage	Second Stage
*Ln(Ventil)*Post*rd*	0.1108***	0.1108***		
	(0.0001)	(0.0001)		
*Target*Post*rd*			0.0066***	0.0830**
*(Ln(Ventil)*Post*rd as IV)*			(0.0005)	(0.0350)
Control variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	589,651	589,651	589,651	589,651

Notes: Standard errors in parentheses. ***p<1%; **P<5%; *p< 10%.

Table 6. Robustness analysis: Testing for industry heterogeneity (Technology distance frontier)

Dependent Variable:	*Target*Post*tecdist*		*Ecoinno*	*Ecoinnop*
	(1)	(2)	(3)	(4)
	First Stage	First Stage	Second Stage	Second Stage
*Ln(Ventil)*Post*IDF*	0.1105***	0.1105***		
	(0.0001)	(0.0001)		
*Target*Post*IDF*			0.0149***	0.0139
*(Ln(Ventil)*Post*IDF as IV)*			(0.0017)	(0.0978)
Control variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	589,651	589,651	589,651	589,651

Notes: Standard errors in parentheses. ***p<1%; **P<5%; *p< 10%.

Table 7. Robustness analysis: Testing for industry heterogeneity (Pollution intensity)

Dependent Variable:	*Target*Post*indpollu*		*Ecoinno*	*Ecoinnop*
	(1)	(2)	(3)	(4)
	First Stage	First Stage	Second Stage	Second Stage
*Ln(Ventil)*Post*indpollu*	0.1133***	0.1133***		
	(0.0001)	(0.0001)		
*Target*Post*indpollu*			0.0020***	0.0246**
*(Ln(Ventil)*Post as IV)*			(0.0002)	(0.0124)
Control variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	494,197	494,197	494,197	494,197

Notes: Standard errors in parentheses. ***p<1%; **P<5%; *p< 10%.

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[1] Flexible policies refer to tradable permits, Pigouvian taxes, deposit/refund systems, and subsidies. They offer incentives to emitters so that their private choice coincides with society's low-carbon choice.

[2] Technology standards is a form of command-and-control direct regulation, where 'command' indicates the mandatory nature of the ambient, technology-based or performance-based standards and 'control' denotes that failure to comply will be penalized.

[3] OECD defines regulatory stringency as "…the explicit and implicit, policy-induced price of environmental externalities" (2015: 22).

[4] We use the wind speed information at the 10-m height and the boundary layer height (used to measure mixing height for the grid of 75*75 cells).

[5] CNIPA provides detailed information on patents, including application number, application date, IPC classification, applicants' names and addresses, inventors' names and patent attorneys' names and addresses.

[6] http://www.wipo.int/classifications/ipc/en/green_inventory/

[7] NBS includes detailed information on firms, such as ownership, location, industry, assets, revenue, investment, profit, export, employment, and cash flow.