Ecological Economics 132 (2017) 104–112

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Analysis

Different Types of Environmental Regulations and Heterogeneous Influence on "Green" Productivity: Evidence from China

Rong-hui Xie *, Yi-jun Yuan, Jing-jing Huang

Faculty of Management and Economics, Dalian University of Technology, Dalian, China

ARTICLE INFO

Article history:
Received 2 March 2016
Received in revised form 31 August 2016
Accepted 26 October 2016
Available online xxxx

Keywords:
China
"Green" productivity
Environmental regulation
The "strong" Porter Hypothesis
Panel threshold model

ABSTRACT

This paper attempts to examine if the "strong" version of Porter Hypothesis is supported in China by investigating how different regulatory instruments and the relative stringency impact "green" productivity. We use a slacks-based measure (SBM) and Luenberger Productivity Index, accounting for undesirable outputs, to evaluate the industrial "green" productivity growth rates of China's 30 provinces. The estimates imply an unsustainable development model in China with significant regional differences. By employing a panel threshold model and a province-level panel dataset during 2000–2012, empirical results show that both command-and-control and market-based regulation have a non-linear relationship with and can be positively related to "green" productivity but with different constrains on regulation stringency: there are double thresholds with the command-and-control and exists an optimal range of stringency for productivity improvement; while a single threshold has been found with the market-based regulation and its current stringency is reasonable for most of provinces. Moreover, based on China's reality, the productivity effect driven by market-based regulation is much stronger than that of the command-and-control. The mechanism of informal regulation is much more complicated. Consequently, we find evidence to support the "strong" Porter Hypothesis that reasonable stringency of environmental regulations may enhance rather than lower industrial competitiveness.

1. Introduction

China has achieved phenomenal growth rates over the last three decades. The growth model, however, turned out to be extensive and unsustainable, which favors economy over the environment. In response to the serious pollution, Chinese government has enacted a series of environmental regulations since 1970s. As environmental regulations will increase the costs of firms and impose constraints on their production activities, it is of fundamental importance to analyze how such regulations affect economic performance, and whether regulations can act as a crucial factor to enhance firms' competitiveness.

Under neoclassical assumptions, the traditional view holds that environmental regulations adversely affect competitiveness by imposing additional burdens on firms. On the one hand, firms face direct costs induced by pollution control activities; on the other hand, with limited financial budgets, firms will incur opportunity costs by committing resources to comply with regulations, rather than invest in other profitable opportunities (Palmer et al., 1995; Gray and Shadbegian, 2003). Porter (1991) and Porter and van der Linde (1995) challenge the conventional wisdom, known as Porter Hypothesis. They argue that well-designed regulations would lead to a Pareto improvement (i.e., improving the environmental quality while not hampering economic performance) or even a "win-win" situation, by not only benefiting the environment, but also enhancing firms' competitiveness through creating incentives for innovations, improving product quality and production processes, and finally offsetting the compliance costs. This proposition has been mainly supported by proponents of a neo-Schumpeterian approach over the last two decades (Peuckert, 2014).

Given the important implications for policy making and economic performance, empirical analysis on proving or disproving the Porter Hypothesis is vast since the early 1990s. To date, however, the literature in this line is scant for developing countries, as most studies focus on US and Europe. This paper employs a province-level panel dataset for the 2000–2012 period to find out empirical evidence on the "strong" version of Porter Hypothesis in the case of China.

We will contribute to the previous literature in several ways. First, unlike the existing literature, this paper employs the environmental TFP to measure firms' competitiveness instead of traditional TFP which has been testified to overestimate the "true" productivity (Zhang et al., 2011). We apply a slacks-based measure (SBM) incorporating emissions as undesirable outputs to estimate the Luenberger

* Corresponding author at: NO.2 Lab Building of Dalian University of Technology, NO.2 in Ling-gong Road, Gan-jing-zi District, Dalian City, China.
E-mail address: sparking_rh@126.com (R. Xie).

http://dx.doi.org/10.1016/j.ecolecon.2016.10.019
0921-8009/

Productivity Index[1]. Second, in order to take both the regulation stringency and instrument design into consideration, we divide environmental regulations into three types, namely the command-and-control, the market-based and the informal regulation[2], and further examine if there appears to have heterogeneous effects on “green” productivity due to different types of regulations. Third, we assume a non-linear relationship between environmental regulations and environmental TFP growth in order to throw light on that given a certain type of regulation, how it affects the environmental TFP and if there exist thresholds or turning points in the regulation-productivity relationship.

The remainder of the paper is structured as follows. Section 2 reviews the literature on “strong” Porter Hypothesis. Section 3 briefly introduces the environmental regulations in China. In Section 4, the estimates of environmental TFP growth rates and two sources are presented, as well as a descriptive statistical analysis. Section 5 describes the specifications of empirical model and variables. Our empirical results and discussions are presented in Section 6. The last section summarizes this study and discusses its policy implications.

2. Literature Review

The Porter Hypothesis has stimulated extensive academic research and policy debates for more than twenty years. Different versions of the hypothesis have been proposed and tested. Jaffe and Palmer (1997) first distinguish among the “weak”, “narrow” and “strong” versions of PH. Given to our objectives, we will mainly focus on studies about the strong version. It rejects the narrow profit-maximizing paradigm and posits that properly designed regulation can actually enhance firms' competitiveness. The shock of a new regulation may signal firms about likely resource inefficiency and potential technological improvements, which may trigger innovation and further partially or more than fully offset the compliance costs.

There is a large body of empirical literature on this topic, however, presents mixed results. Early studies mostly conclude that environmental regulations cause a loss of productivity. Barbera and McConnell (1990) find that, in five heavily polluting U.S. industries, the effect of abatement costs on productivity is significantly negative, accounting for about 10%–30% of productivity decline. Boyd and McClelland (1999) point out that expenditures on pollution abatement crowd out other efficient investments and thus reduce production by 9.4% in U.S. paper industry. This result is quite close to that of Gray and Shadbegian's (2003) who conclude a regulation-induced productivity decline of 9.3% in a typical integrated U.S. mill industry. While Greenstone et al. (2012) claim that stringent air quality regulations are associated with a roughly 2.6% decline in the TFP of U.S. manufacturing plants. Over the country-level, Rubashkina et al. (2015) employ a panel data of 17 European countries, but still find no evidence in favor of the strong PH. Rexhäuser and Rammer (2014) conclude that the strong PH does not hold in general, rather the impact of regulations on competitiveness is heterogeneous depending on the type of environmental innovation.

More recently, numerous studies have provided clearer support on the strong PH (Brännlund and Lundgren, 2009), and draw cautiously optimistic conclusions (Berman and Bui, 2001; Alpay et al., 2002). Using energy taxes intensity to proxy regulation stringency in manufacturing sectors of 7 European countries, Franco and Marin (2013) find that the effect of regulation on productivity is statistically significant and direct. Rassier and Earnhart (2015) identify a positive relationship between tighter clean water regulation and actual profitability in the chemical manufacturing industries in U.S. Both Lanoie et al. (2008) and Peuckert (2014) consider the dynamic aspect of the hypothesis and demonstrate a negative effect in the short term, but positive long-run impacts on firm's productivity growth. Telle and Larsson (2007) are perhaps the first to use an environmental Malmquist productivity index (EMI) accounting for emission reductions as inputs when investigating the relationship between environmental regulations and competitiveness, and find a positive and statistically significant productivity effect. Similarly, Zhang et al. (2011) employ the Malmquist-Luenberger productivity index incorporating undesirable outputs to estimate China's environmental TFP growth and corroborate the strong PH in China.

The conflicting evidence could be caused by a number of factors and several aspects are worth to note concerning the previous studies. Firstly, Porter and van der Linde (1995) emphasize the importance of well-designed regulatory instruments for the effect of “innovation offsets”. While either Kemp (1997) claims that there is no best regulatory instrument, or Frondel et al. (2007) claim that regulatory stringency is much more important than instrument design. Iraldo et al. (2011) provide a helpful summary that the form of regulation may be as important as its stringency in determining the nature of its relationship with economic performance. However, few empirical studies explore these two aspects jointly. Moreover, most studies only examine one type of regulation, while fail to distinguish the potentially different effects among different types of regulatory mechanisms. Secondly, Koźluk and Zipperer (2013) point out that the strong PH is usually very context-specific and hence can only provide limited general conclusions. Most previous literature focuses on highly developed economies, but lacks of evidence from developing countries, such as China who is suffering worse pollutions while facing with greater pressures on economic growth. Thirdly, Lankoski (2010) demonstrates the pivotal role of certain methodological features and notes that previous studies have identified fifty or more methodological or measurement problems that make it difficult to draw conclusions. Jin (2009) points out that the capability of firms to bear increased compliance costs is limited in a certain time. Neither the regulation being too lax nor too harsh is able to trigger effective incentives on economic performance. It suggests that there may be a non-linear relationship. However, most previous studies only assume a linear relationship. This study helps fill that gap. Finally, Ambec et al. (2013) conclude that more empirical support for the strong PH in recent studies may be simply because the world has changed over time, which means that firms are more able to profit from their environmental initiatives than in the past and that the PH may be more relevant today.

3. Environmental Regulations in China

After the Human Environmental Conference in Stockholm in 1972, China initially enacted its first Environmental Protection Act. From then on, a series of environmental statutes gradually came into effect, such as the Water Pollution Control Act in 1994, the Noise Pollution Control Act in 1996, the Air Pollution Control Act in 2000, and the Radioactive Pollution Prevention and Control Act in 2003. By 2005, when the Waste Disposal Act was legislated, the environmental statutes seemed to be complete in China.

In general, environmental regulations in China can mainly be divided into three different types, namely the command-and-control, the market-based and the informal regulation.

3.1. Command-and-control Regulation

Basically, China's environmental regulations have been largely command and control. Government sets emission standards for almost all kinds of pollutants and plants emitting pollutions that exceed the emission standards will be fined, or even forced to shut down. For example, a typical command-and-control regulation in China is to force small energy- and emission-intensive enterprises

[1] The terms of “bads”, “bad output”, “undesirable output” and “pollution” in this paper are used interchangeably, while terms of “goods”, “good output”, and “desirable output” are interchangeable as well.

[2] Corresponding to informal regulation, the command-and-control and market-based regulation can be collectively referred to as formal regulations.

to close down, to suspend operation, to merge with others or to shift to different line of production (*guan ting bing zhuan*) which implemented in 1990s. As a result, 84,000 small energy- and emission-intensive enterprises were compelled to close during 1996–2000 and 33,000 closed during 2001–2005 (Chen, 2010). The main characteristic of command-and-control regulation is coerciveness which depends on administrative measures.

Stringent environmental standards can push firms to realize their inefficiency and to search for pollution abatement measures, such as discovering new end-of-pipe techniques, increasing resource efficiency, and switching to clean energy. Once firms satisfy such standards, however, there will be no further motivation for them to initiate R&D efforts, especially concerning policies of technical standards. Moreover, owing to information asymmetry, firms tend to hide emission information, or even break the law to discharge excess emissions stealthily, in order to shirk environmental supervision and lower environmental costs.

3.2. Market-based Regulation

The market economic reforms of China proceeded in 1980s provide institutional foundations for market-based regulation which include two major policies, that is, pollutant discharge fees and tradable emissions. According to the principle of "polluter pays", China imposed the pollutant discharge fees in 1982. It becomes the primary market-based regulation in China, as well as one of the main sources of funds for the pollution treatment, showing a continuously sharp growth during 1996–2012 (increased from 7.43 billion in 1996 to 18.89 billion in 2012). Tradable emissions are still in its pilot stage and only implement in several provinces and cities. In 1999, China carried out the SO_2 emission trading in Nantong City and Benxi City for the first time. Until 2008, Shanghai Environment and Energy Exchange (SEEEX), China-Beijing Environment Exchange (CBEEX) and Tianjin Climate Exchange (TCX) have been founded in succession to control emissions like CO_2, SO_2, COD and mental pollutants.

3.3. Informal Regulation

The third type of environmental regulations is the informal regulation. It is not imposed by the government, but depends on public environmental awareness. Nowadays, there is a growing interest in the potential of informal regulation to achieve environmental goals, especially when formal regulations are weak or absent in developing countries. Pargal et al. (1997) indicate that communities are often able to negotiate with or informally pressure polluting plants in their vicinity to clean up. They point out that the informal regulation includes demands for compensation by community groups, social ostracism of the firm's employees, boycotts of the firm's product, and efforts to monitor and publicize the firm's emissions. Kathuria (2007) points out that press can function as an informal regulator since the discussions and reports on pollution in the vernacular press can influence localized pollution. Langpap and Shimshack (2010) consider informal regulation as the actions of private groups suing government agencies or individual polluters to enforce statutory requirements.

The objective for citizen involvement in environmental regulation is to increase public enforcement by bringing attention to instances of non-compliance and illegal behavior. As a result, informal regulation will impact firms' reputation which certainly has further effect on their stock and market performance. Although most of the major environmental statutes in China provide the public with rights of supervision and citizen suits, public environmental awareness is still weak; environmental NGOs are powerless; and the role of communities are almost absent in China, compared to developed countries.

4. Measuring the Environmental TFP Growth

4.1. Methodology

Based on the pioneering work of Chung et al. (1997), many researchers employ the directional distance function (DDF) to address the issue that simultaneously credits reductions in 'bads' and increases in goods[3]. Fukuyama and Weber (2009), however, point out that if there exist slacks, the DDF will underestimate the technology inefficiency[4]. Therefore, following the research of Fukuyama and Weber (2009) and Wang et al. (2010)[5], this paper uses a directional slacks-based measure (SBM) to estimate the production frontier. Linear programming is used to calculate the value of the SBM distance function for each decision-making unit (DMU) at a fixed point in time (as detailed in Appendix A). Furthermore, we use the Luenberger Productivity Index proposed by Chambers et al. (1996) to measure the environmental TFP (*ETFP*) of China's 30 provinces over the period of 2000–2012[6].

The desirable output is given by total industrial output value (*TIV*) measured at 1999 prices, and the undesirable output is given by CO_2 emissions. Data on *TIV* are obtained from China Industry Economy Statistical Yearbook (2000 − 2013). Since the data on CO_2 emissions cannot be obtained directly, we consider the approach proposed by Chen and Golley (2014) to calculate it. The energy-induced CO_2 emissions only take into account the emissions generated directly from the combustion of three primary fossil energy (coal, petroleum and natural gas); that is, total (direct) energy consumption[7]. Each energy has a different emission factor. Multiplying the consumption of each energy source by its emission factor and summing across all sources, we finally get the data of CO_2 emissions. Data on energy consumption of coal, petroleum and natural gas is obtained from China Energy Statistical Yearbook (2000–2013). Besides, three inputs are included corresponding to capital, labor and energy. The labor force is given by the number of employed workers which can be found in China Labour Statistical Yearbook (2000–2013). In some analyses which take emissions into account, researchers consider energy as an intermediate input and the main source of emissions as well (Watanabe and Tanaka, 2007; Wang et al., 2010). We choose to follow their lead. The capital stock is usually estimated by using the perpetual inventory approach in the preceding researches. However, this approach has a very high requisition for data which is difficult to obtain for industrial sectors of China (Dong et al., 2012). Therefore, we consider the net value of the investment in fixed assets at 1999 prices as a proxy.

4.2. Results of Environmental TFP and Its Sources

First of all, the thirty provinces of China are aggregated into three economic zones, namely Eastern China (with 11 provinces), Middle of

[3] The null-jointed assumption implies that producing good outputs require the production of "bads". The weak disposability of outputs denotes that the abatement of bad outputs is costly by giving up good outputs. For the detailed explanations about the DDF and assumptions, see Färe et al. (2007) and Wang et al. (2008).

[4] Fukuyama and Weber (2009) explore the relationship between SBM and DDF: When there are no slacks in the constraints defining the technology, the SBM is equal to the DDF; however, when such slacks exist, the SBM is no less than the DDF. Since the DDF is not able to capture the slacks, it often underestimates the technology inefficiency.

[5] Fukuyama and Weber (2009) only include desirable outputs. Wang et al. (2010) expand their work by incorporating the undesirable outputs.

[6] The thirty province-level regions are the twenty-two provinces, four autonomous regions and four municipalities in mainland China. Tibet has been eliminated because of its missing data.

[7] Following Chen and Golley (2014), we only account for emissions generated directly from the combustion of three primary fossil energy, but not the emissions generated indirectly via other inputs that themselves use energy in their production processes (including electricity), nor those emissions generated via industrial processes. This approach is very similar to China's fossil-fuel related CO_2 emissions provided by IEA (http://www.iea.org/statistics/topics/CO2emissions/). See Chen and Golley (2014) for further details, while more discussion of the various methods for measuring energy-induced emissions in the Chinese context can be found in Golley and Meng (2012).

Table 1
Average annual growth rates of outputs, inputs and productivity (2000 − 2012) (%).
Source: Dataset described in the text and authors' calculations.

Regions	*TIV*	CO_2	Labor	Capital	Energy	*ETFP*	Contributions of *ETFP* to *TIV* growth
Eastern China	19.67	8.82	1.97	9.76	9.37	3.14	15.96
Middle of China	22.95	7.93	−1.59	11.37	8.71	3.12	13.59
Western China	22.39	14.31	−0.75	12.17	10.37	2.36	10.54
All	21.60	10.59	0.02	11.07	9.56	2.85	13.19

Notes to the table: The values of contribution of *ETFP* to *TIV* growth are calculated following Wu (2008) by dividing the *ETFP* growth rate by the *TIV* growth rate.

China (with 8 provinces) and Western China (with 11 provinces), in accordance with the regional partition method proposed in the Seventh Five-year Plan in 1986.

The first five columns of Table 1 report the annual growth rates of outputs and inputs averaged over the region-level. The data shows that China witnesses an annual averaged increase in *TIV* growth of 21.6%, with Middle of China experiencing the highest value of 22.95% and the lowest value of 19.67% in Eastern China. Capital and energy consumption are clearly the dominant contributors to *TIV* growth that the aggregate annual averaged growth rates are 11.07% and 9.56%, respectively. The combination of growth rates of energy and CO_2 emissions demonstrates that China's industrial economy depends heavily on energy consumption and results in serious environmental damage. The growth rates of labor are very low (only 0.02%) and even negative in Middle of and Western China (−1.59% and −0.75%, respectively). This might be blame to the laid-off tide caused by China's deep ownership reforms at the beginning of 21th century. The fact that the Eastern China is observed the highest and the only positive annual labor growth of 1.97% can be explained by the large labor migration from inland to East in 1990s.

The final two columns of Table 1 report the estimated annual growth rates of *ETFP* and contributions to *TIV* growth[8]. The aggregate *ETFP* growth rate is 2.85%, and its contribution to *TIV* growth is 13.19%. Generally, the share of *ETFP* in output growth is taken as the criterion if the economy has transformed towards a more sustainable model. However, the data above implies that the development model of China's industrial economy is extensive and unsustainable during 2000–2012.

Of the three economic zones, Eastern China achieves the highest *ETFP* growth rate (3.14%), as well as the highest share in output growth (15.96%), which suggests a relatively more intensive growth model. In Western China, the combination of its extremely rapid *TIV* growth (22.39%) and the highest energy consumption growth (10.37%) explains the dramatic surge in CO_2 emissions with annual averaged growth rate of 14.31%, which offers an explanation for the lowest *ETFP* growth (2.36%), as well as the lowest contribution to *TIV* growth (10.54%). It signifies that, due to its abundant resources endowment, the growth pattern in Western China is of particular extensive and puts heavy threat on environment. Therefore, how to break through the dilemma of "Resource Curse", and how to transform to "green" development pattern, are big challenges for China in the future.

Table 2 presents environmental TFP growth rates and two sources for each province between 2000 and 2012 which reveal significant differences at provincial level. For example, Shandong witnesses the highest growth rates of *ETFP* (4.31%), followed by Beijing and Jiangxi which both are 4.26%, while the lowest is observed in Hainan recording a negative value of −1.47%. Technical progress is the dominant source of *ETFP* growth in virtually all provinces over this period, peaking at 3.78% in Jiangsu, followed by Shanghai (3.64%) and Zhejiang (3.25%), which all locate in the Yangtze River Delta region. Efficiency change remains low and even negative in some provinces. Beijing and Qinghai witness the highest (2.26%) and the second highest (2.07%) value of *Effe*, while at the other extreme, it reports −0.73% in Ningxia, and −0.14% in Zhejiang. Overall, provinces reporting higher growth rates of *ETFP* and *Tech* mainly locate in Eastern China. It confirms that Eastern China has achieved more advanced technology and better environmental performance than inland provinces. However, the *Effe* of Middle of China (1.13%) is superior to the other two economic zones, indicating a catching-up effect to the production frontier.

Indeed, no matter the aggregate results or the province-level results, they both suggest that China is not yet on the path towards "green" and sustainable growth since the contribution of *ETFP* to output growth is well below the 50% mark taken to signal a successful transition to a low-carbon economic model (Chen and Golley, 2014).

5. Empirical Model and Variables

5.1. Specifications of the Panel Threshold Model

Referring to previous studies (e.g. Yang et al., 2012), the empirical model is specified the log-log form and the estimated coefficient can be interpreted as the elasticity with respect to environmental TFP growth. In order to examine the non-linear regulation-productivity

Table 2
Annual growth rates of *ETFP* and its sources (2000–2012).
Source: Authors' calculations with Max DEA software.

	Provinces	*ETFP*	*Effe*	*Tech*
Eastern China	Beijing	1.0426	1.0226	1.0194
	Tianjin	1.0362	1.0152	1.0201
	Hebei	1.0281	1.0059	1.0221
	Liaoning	1.0388	1.0178	1.0209
	Shanghai	1.0361	0.9997	1.0364
	Jiangsu	1.0378	1.0000	1.0378
	Zhejiang	1.0328	0.9986	1.0325
	Fujian	1.0334	1.0069	1.0240
	Shandong	1.0431	1.0171	1.0256
	Guangdong	1.0323	1.0000	1.0323
	Hainan	0.9853	1.0000	0.9853
	Mean	1.0314	1.0076	1.0232
Middle of China	Shanxi	1.0216	1.0051	1.0164
	Jilin	1.0352	1.0162	1.0187
	Heilongjiang	1.0176	0.9969	1.0204
	Anhui	1.0341	1.0138	1.0200
	Jiangxi	1.0426	1.0263	1.0132
	Henan	1.0313	1.0082	1.0229
	Hubei	1.0304	1.0069	1.0227
	Hunan	1.0373	1.0168	1.0200
	Mean	1.0312	1.0113	1.0193
Western China	Inner Mongolia	1.0352	1.0190	1.0162
	Guangxi	1.0319	1.0112	1.0187
	Chongqing	1.0329	1.0172	1.0152
	Sichuan	1.0385	1.0178	1.0204
	Guizhou	1.0139	0.9974	1.0164
	Yunnan	1.0172	0.9962	1.0202
	Shanxi	1.0217	1.0004	1.0208
	Gansu	1.0226	1.0040	1.0182
	Qinghai	1.0389	1.0207	0.9974
	Ningxia	0.9849	0.9927	1.0082
	Xinjiang	1.0231	1.0046	1.0176
	Mean	1.0236	1.0073	1.0154

Notes to the table: Since some of the estimates of *ETFP*, *Effe* and *Tech* are in negative values and a simple calculation for geometric means is not possible, the data of the three indicators all plus one, such as (1 + *ETFP*) to make the observations positive (Managi and Jena, 2008).

[8] The annual averaged growth rates of ETFP and two sources of efficiency change (*Effe*) and technical progress (*Tech*) below are all geometric means.

relationship, we employ the fixed-effect panel threshold model proposed by Hansen (1999). Taking a single-threshold model as an example, the specification is as follows[9]:

$$\ln ETFP_{i,t} = \beta_0 + \beta_{11}\ \ln ER_{i,t-1}\cdot I(q_i \le \gamma) + \beta_{12}\ \ln ER_{i,t-1}\cdot I(q_i > \gamma) + \varphi Z_{i,t-1} + v_i + \varepsilon_{i,t} \quad (1)$$

where $I(\cdot)$ is the indicator function. *ER* indicates the independent variables, referring to the vector of stringency of command-and-control, market-based, and informal regulation. The observations are divided into two regimes depending on whether the threshold variable q_i is lower or higher than the threshold value γ.The regimes are distinguished by differing regression slopes, β_{11} and β_{12}. $Z_{i,t-1}$ denotes a vector of control variables. The subscripts *i* and *t* denote province and year. Individual (province) effects are captured by v_i and $\varepsilon_{i,t}$ is the disturbance term. As environmental TFP growth requires changes in technology and/or production processes which will take time to be effective, it appears reasonable that there exists a time lag between environmental regulations and changes in environmental TFP. Therefore, we allow one-year lag in the variables of regulation stringency. Moreover, all of the control variables are lagged one year to avoid two-way causation with productivity (Rubashkina et al., 2015)[10].

5.2. Variables and Data Source

The main purpose of this study suggests the importance of adequate measures of regulation stringency. The common approach in the existing literature is to use pollution abatement and control expenditures (PACE) as a proxy for stringency of formal regulations (Brunneimer and Cohen, 2003; Hamamoto, 2006), while Yang et al. (2012) include both PACE and pollution abatement fees (PAF). Obviously, this can be problematic in our case since neither PACE nor PAF enables us to divide formal regulations into two different types mentioned above. In this paper, we use Environmental Investments in New Construction Projects (*EI*) as a proxy for stringency of the command-and-control regulation, and pollutant discharge fees (*PDF*) as a proxy for the market-based regulation.

The measurement for stringency of the informal regulation, the situation is much more challenging. Pargal and Wheeler (1996) consider four variables, that is, per capita income, community education, population density, and plant share of local employment. Goldar and Banerjee (2004) point out that education, degree of political organization and environmental awareness are considered to be important factors determining the stringency of informal regulation. They use the poll percentage and the rate of increase in literacy level in a district as indicators of informal regulation. Kathuria (2007) indicates that informal regulation can be measured by the number of articles on pollution in the vernacular and national press. Langpap and Shimshack (2010) use citizen suit records as a proxy variable. Owing to limitation of data, this paper employs the number of public complaints about pollution events (*complaint*) and education level of employees (*EDU*) as proxies for stringency of the informal regulation[11].

Six control variables of interest for our investigation are included. Firstly, foreign direct investment (*FDI*) plays an essential role in China's economy. The mechanism of *FDI* influencing environmental TFP is complicated and uncertain. On the one hand, *FDI* can bring advanced techniques to the host country through technology spillover effect. On the other hand, however, it has been proved that *FDI* also increases emissions and leads to Pollution Haven effect (List et al., 2000). Secondly, patents (*PAT*) capture the technological capacity which is expected to have a positive influence on *ETFP*. Thirdly, we include a variable of ownership structure (*OWNERS*) defined by the output shares of state-owned enterprises (SOEs). Fourthly, export intensity (*EXP*) captures a region's international linkage. Since the international market is generally more competitive than the domestic market, the keen competition abroad can encourage activities aiming at productivity improvement through learning-by-exporting effect (Kneller and Manderson, 2012). Fifthly, a scaling variable (*SCALE*) is included, defined as ratio of industrial output to regional GDP. Finally, we use the level of infrastructure (*ENDOW*) which is measured by geometric average length of road and rail of every square kilometers of each province to reflect the characteristics of regional endowment (Wu, 2008).

Table 3
Descriptive statistics of key variables.

Variable	Obs	Mean	S.D.	Minimum	Maximum
ETFP	390	1.22	0.22	0.64	1.81
EI (RMB 10 million *yuan*)	390	442.29	1391.16	0.51	13,778.10
PDF (RMB 10 thousand *yuan*)	390	22,555.16	19,466.58	666.06	140,242.70
complaint	390	19,410.79	22,073.37	50.00	147,493.00
EDU	390	8.74	1.18	6.11	13.31
FDI (%)	390	0.47	0.58	0.05	5.71
PAT	390	21,319.18	44,418.52	124.00	472,656.00
OWNERS (%)	390	0.50	0.21	0.11	0.94
EXP (%)	390	0.17	0.20	0.01	0.91
SCALE (%)	390	0.39	0.08	0.13	0.53
ENDOW (km per square km)	390	0.10	0.07	0.01	0.39

Notes to the table: To avoid the possibility of insignificance caused by *ETFP* changing near 0, the *ETFP* indices are transformed into their accumulated form and then their logarithmic form in empirical regression following Managi and Jena (2008) and Wang et al. (2010). Since some of the estimates of *ETFP* are in negative values, the *ETFP* data are converted into (1 + *ETFP*) forms to ensure the estimates positive.

Table 3 summarizes the descriptive statistics of key variables. The province-level panel data during the period 2000–2012 is obtained from the database of the National Bureau of Statistics of China. All nominal variables are deflated into real ones by using the GDP deflator index for the year 2000.

6. Empirical Results and Discussions

6.1. Results of Threshold Effect Tests

In order to examine if significant non-linear relationship exists, and further determine the number of thresholds, we follow the bootstrapping method proposed by Hansen (1999) to obtain the approximations of the *F* statistics and then calculate the *p*-value[12]. The *F* statistics assess the null hypotheses of none, one and two thresholds, respectively. We regard the estimated threshold as the "turning point" in the non-linear regulation-productivity relationship. Once one or more significant thresholds are found, we can divide the regulation stringency into different regimes and estimate the coefficient for each regime. According to Hansen (1999), the threshold variable q_i may be an element of independent variables x_i. For the purpose of our analysis, this paper uses indexes of regulation stringency as the threshold variables.

Table 4 presents results of the single, double, and triple threshold effect tests. We find that: (1) For the command-and-control regulation, the bootstrap *p*-value for a single threshold is insignificant at 0.4300, while the test for a double threshold is highly significant with a *p*-value

[9] Two statistical tests are needed with the panel threshold model: (1) To test for a threshold with the null hypothesis of no threshold effect: H_0:β_{11}=β_{12}. (2) When there is a threshold effect ($\beta_{11}\neq\beta_{12}$), we need to use the likelihood ratio statistic to test that $\hat{\gamma}$ is consistent for γ_0 (the true value of γ) with the null hypothesis: $H_0 : \hat{\gamma} = \gamma_0$. More details can be found in Hansen (1999).

[10] For example, through the self-selection effect, higher productivity could cause higher exporting. While the causality between productivity and *SCALE* could also be bidirectional, since productivity enhancement could cause a boost of production.

[11] The public complaints include letters, over phone calls, and through the internet. While the indicator of *EDU* is measured $EDU_i = p_{i1}\times 6 + p_{i2}\times 9 + p_{i3}\times 12 + p_{i4}\times 16$, where p_{i1}, p_{i2}, p_{i3}, and p_{i4} denote the ratio of employees in province *i* graduated from primary school, junior high school, senior high school, and university or above respectively, weighted by corresponding schooling years.

[12] Details for estimation techniques of panel threshold models are provided in Hansen (1999).

Table 4
Results of threshold-effect tests.

Threshold variables	Single (H_0: no threshold)		Double (H_0: at most one threshold)		Triple (H_0: at most two thresholds)	
	F-statistic	*p*-Value	*F*-statistic	*p*-Value	*F*-statistic	*p*-Value
ln*EI*	12.63	0.4300	42.11**	0.0200	7.26	0.6700
ln*PDF*	57.26***	0.0000	19.88	0.1100	4.58	0.9300
ln*complaint*	23.93**	0.0167	22.01**	0.0367	4.55	0.7367
ln*EDU*	40.37*	0.0533	17.56	0.2567	15.14	0.5767

Note: Table 4 reports *F*-test of the null hypothesis of no threshold effect and bootstrapped *p*-value obtained from 300 bootstrap replications. ***, **, * indicate that the levels of significance are 1%, 5% and 10%, respectively.

of 0.0200. Therefore, the empirical result implies two thresholds. (2) For the market-based regulation, only the *p*-value for a single-threshold model is highly significant at 0.0000. (3) When concerning the informal regulation, a double threshold effect is significant at 5% level, with ln*complaint* as the threshold variable; while only the single-threshold test is significant with a bootstrap *p*-value of 0.0533 with ln*EDU* as the threshold variable.

Table 5 further reports the estimated values of thresholds and their confidence intervals. Take the command-and-control regulation as an example. Table 5 presents the estimated values of two thresholds ($\hat{\gamma}_1$, $\hat{\gamma}_2$), 2.0794 and 2.1748, respectively. Thus, all observations of the command-and-control regulation stringency will be objectively split into three regimes: *a low EI regime* with ln*EI* ≤2.0794, *a moderate EI regime* for those with ln*EI* between 2.0794 and 2.1748, and *a high EI regime* with ln*EI* exceeding 2.1748. The same procedure may be easily adapted to divide observations of the market-based regulation stringency into two regimes, i.e. *a low PDF regime* (ln*PDF* ≤7.8017) and *a high PDF regime* (ln*PDF*>7.8017), and to split the informal regulation stringency based on relative threshold estimates.

6.2. Estimation Results of the Threshold Model

Once the threshold values are estimated, we can regress the panel threshold model. As the estimation results of a double-threshold model demonstrated in Model (1) of Table 6, the non-linear relationship between command-and-control regulation and *ETFP* growth with two turning points has been proved. For the low *EI* regime, i.e. *EI* ≤7.9997 (RMB 10 million *yuan*)[13], the coefficient of ln*EI* is 0.0142 but insignificant, while the coefficient of ln*EI* equals to 0.1571 and highly significant at the 1% level for the moderate *EI* regime (7.9997<*EI* ≤8.8004). In the high *EI* regime (*EI*>8.8004), the *EI* elasticity equals to 0.5500% and marginally significant at the 10% level. The results provide evidence for the strong PH of a possible win-win situation in the case of command-and-control regulation only if ln*EI* crosses the first threshold. Furthermore, there exists an optimum range for the stringency of command-and-control regulation to motivate *ETFP* growth. When the command-and-control regulation is relatively lax, it will not be able to induce effective incentives on *ETFP* growth; while being too harsh, the incentive effect is positive, but very small. Only when its stringency falls into a specific interval, will it induce the optimal incentives for *ETFP* growth. According to the annual averaged data from 2000 to 2012, we can find that the Environmental Investments in New Construction Projects of all 30 provinces have been crossed the second threshold of 8.8004 and locate in the high *EI* regime, with a maximum value in Shandong (2181.68) and a minimum value in Gansu (32.74). It implies that China's current command-and-control regulation has been stricter than the optimal level so that its incentive effect on environmental TFP growth is weak and limited.

Model (2) in Table 6 reports the estimation results of a single threshold model in case of the market-based regulation. It also confirms a non-linear relationship between the stringency of market-based regulation and the *ETFP* growth with one turning point. For the low *PDF* regime, i.e. the value of *PDF* ≤2444.7550 (RMB 10 thousand *yuan*), stricter market-based regulation is associated with higher *ETFP* growth with the coefficient of ln*PDF* being 0.0403 and significant at the 5% level. When the value of *PDF* crosses the threshold, i.e. in the high *PDF* regime, however, there is no effective influence on *ETFP* growth since the coefficient of ln*PDF* is far from significant. The annual averaged data of *PDF* of China's 30 provinces shows that twenty-two provinces belong to the low *PDF* regime, while only eight provinces fall into the high *PDF* regime which contain the typical resource-based provinces such as Hebei (43,034.76) and Shanxi (59,321.85), as well as the typical economy-developed provinces such as Jiangsu (68,472.96), Zhejiang (44,448.72), Shandong (50,685.33) and Guangdong (41,602.22). China's pollution discharge fees were enacted in 1979 and revised in 2003. Many researchers, such as Hou and Chen (2013), point out that the current standards of pollution discharge fees in China are far from effective for pollution abatement. However, we are not consistent with this view of point. In the economic-performance perspective, our results show that the current level of *PDF* is reasonable since it has a significantly positive effect on *ETFP* growth for most of the provinces.

Crucially, in the Chinese context, all 30 provinces fall into the high *EI* regime with coefficient of 0.0055, while most of provinces fall into the low *PDF* regime with coefficient of 0.0403. Compared the effect of command-and-control regulation on *ETFP* growth with that of market-based regulation, it manifests that incentives on *ETFP* growth induced by the latter are much more effective than the former. It is because the command-and-control regulation generally requires firms to reach a certain environmental standard, or to employ a certain kind of pollution abatement technique. In this case, most firms prefer to take a one-time behavior for a long period, such as simply buying end-of-pipe equipment, rather than engage in costly R&D activities. Alternatively, pollutant discharge fees rivet greater firms' attention not only on pollution abatement but also on pollutant emissions. Moreover, the pollutant discharge fees are persistent expenditures for regulated firms who may be fairly conscious of heavier operating cost burdens. As a result, the pollutant discharge fees are more effective in converting social costs induced by pollution into firms' private costs, and driving firms to search more fundamental solutions, such as undertaking R&D activities, optimizing their resource allocation, and reconfiguring the products and processes.

Table 7 reports the estimates of effects of informal regulation on *ETFP* growth. Results in Model (3) show that the coefficients for any of the *complaint* regime are far from significant, indicating that China's current public complaints about pollution events have little effect on firms' behavior. It might be because Chinese citizens still lack of environmental awareness to adopt legal ways to express their preference on environment quality. Indeed, estimates in Model (4) confirm a significant non-linear relationship between ln*EDU* and *ETFP* with one turning point. It indicates that *EDU* has an important impact on environmental TFP growth because citizens with higher level of education will be more aware of the value of improving environmental performance, as well as be more capable of pressuring on government and plants to deal with pollution.

7. Conclusions and Policy Implications

This study attempts to find out if there will be evidence on the "strong" version of Porter Hypothesis in the case of China by examining whether different types of environmental regulations influence

[13] With ln*EI* = 2.0794, we can obtain the threshold value with *EI* = exp(2.0794) = 7.9997 (RMB 10 million *yuan*). Values of other turning points will be calculated similarly hereinafter.

Table 5
Results of threshold estimators and the confidence intervals (level = 0.95).

	ln*EI*		ln*PDF*	
	Threshold estimators	Confidence intervals	Threshold estimators	Confidence intervals
Single	2.0794	[1.9879, 2.2661]	7.8017	[7.6976, 7.8415]
Double	2.1748	[1.9482, 2.1861]		
	ln*complaint*		ln*EDU*	
	Threshold estimators	Confidence intervals	Threshold estimators	Confidence intervals
Single	7.6962	[7.6788, 7.8571]	2.0234	[2.0214, 2.0281]
Double	7.7919	[7.5262, 7.8116]		

environmental TFP growth heterogeneously and if so, whether there exists an optimal level of stringency given a certain type of regulation.

Both the aggregate and the province-level results of *ETFP* growth rates suggest that China has not been on the path towards "green" growth yet and that there exists significant regional differences. We further conduct an empirical analysis by employing a fixed-effect panel threshold model and a panel dataset of China's 30 provinces during the period 2000–2012, and draw interesting and important findings. On the one hand, the threshold regression results of formal regulations support the "strong" version of Porter Hypothesis that formal regulations can be positively related to industrial environmental TFP growth, but with different constrains on command-and-control and market-based regulation stringency. Specifically, there are two turning points in the non-linear relationship between the command-and-control regulation and *ETFP* growth and exists a certain range of stringency to induce optimal incentives. However, all 30 provinces in China have been crossed the optimal range, suggesting the stringency of China's current command-and-control regulation being a little bit harsher than the optimal level. While a single threshold has been found with the market-based regulation and its current stringency is reasonable for most of the provinces. Moreover, based on China's reality, the stimulation on environmental TFP growth driven by market-based regulation is much stronger than that of the command-and-control. On the other hand, informal regulation plays an important and effective role in motivating *ETFP* growth, but only in terms of education level, not public complaints, implying that education plays an important role in informal regulation's mechanism of action.

From the above analysis, this study derives several policy implications. Firstly, the significant regional differences in environmental TFP growth rates and the share in outputs indicate that China's inland in the future must avoid a repeat of the eastern region's model of "pollution first, treatment later". This requires Chinese government to devote more efforts to conduct more prudent and deliberate policy design, in order to prevent the possibility of pollution transfer and to seize the opportunity to go "green". Secondly, China should consider formal regulations as an effective spur to drive China on a truly sustainable path in the future, rather than fear the reverse. What calls for special attention is that a win-win situation can be achieved only if the regulations would be proper, which refers not only to well-crafted regulatory instruments but also to reasonable regulation stringency. Choosing well-crafted regulatory instruments contains two meanings: (1) Compared to developed economies, China still lacks of experience with market-based regulation, the form advocated by Porter. Chinese government should pay more attention to reform and innovate the environmental regulation system; that is, changing the dominant role of the command-and-control and allowing market mechanism work better. The emission trading system should be completed and implemented nationwide. Meanwhile, Chinese government should promote the reform of

Table 6
Threshold model regression: Effects of formal regulations on *ETFP* growth.

Model (1)		Model (2)	
Variable	Double threshold model	Variable	Single threshold model
ln*EI*≤2.0794	0.0142	ln*PDF*≤7.8017	0.0403**
	(0.0111)		(0.0163)
2.0794< ln*EI*≤2.1748	0.1571***	ln*PDF*>7.8017	0.0052
	(0.0205)		(0.0135)
ln*EI*>2.1748	0.0055*		
	(0.0031)		
ln*FDI*	−0.0488***	ln*FDI*	−0.0695***
	(0.0144)		(0.0147)
ln*PAT*	0.1014***	ln*PAT*	0.0829***
	(0.0118)		(0.0118)
ln*EXP*	0.0570***	ln*EXP*	0.0640***
	(0.0140)		(0.0137)
ln*SCALE*	0.1731***	ln*SCALE*	0.2052***
	(0.0492)		(0.0538)
ln*ENDOW*	0.0423	ln*ENDOW*	0.0620*
	(0.0327)		(0.0346)
ln*OWNERS*	−0.0644**	ln*OWNERS*	−0.0837***
	(0.0275)		(0.0261)
Constant	−0.4160**	Constant	−0.2447
	(0.1742)		(0.2543)
Within R^2	0.7616	Within R^2	0.7654
F-test	113.92***	*F*-test	131.35***
F-test all $v_i = 0$	40.66***	*F*-test all $v_i = 0$	32.39***

Notes to the table: (a) The results are calculated by STATA 14.0 software; the command is proposed by Wang (2015). (b) Figures in parentheses are standard error. (c) ***, **, * indicate that the levels of significance are 1%, 5% and 10%, respectively.

Table 7
Threshold model regression: Effects of informal regulation on *ETFP* growth.

Model (3)		Model (4)	
Variable	Double threshold model	Variable	Single threshold model
ln*complaint* ≤ 7.6962	0.0047	ln*EDU* ≤ 2.0234	0.3797***
	(0.0084)		(0.1154)
7.6962 < ln*complaint* ≤ 7.7919	−0.0012	ln*EDU* > 2.0234	0.3146***
	(0.0093)		(0.1111)
ln*complaint* > 7.7919	0.0006		
	(0.0060)		
ln*FDI*	−0.0525***	ln*FDI*	−0.0370**
	(0.0157)		(0.0151)
ln*PAT*	0.1030***	ln*PAT*	0.0997***
	(0.0130)		(0.0131)
ln*EXP*	0.0616***	ln*EXP*	0.0639***
	(0.0153)		(0.0143)
ln*SCALE*	0.1420***	ln*SCALE*	0.1582***
	(0.0521)		(0.0493)
ln*ENDOW*	0.0313	ln*ENDOW*	0.0377
	(0.0360)		(0.0332)
ln*OWNERS*	−0.0878***	ln*OWNERS*	−0.0661**
	(0.0297)		(0.0280)
Constant	−0.4805**	Constant	−1.0674***
	(0.1881)		(0.2604)
Within R^2	0.7196	Within R^2	0.7472
F-test	91.51***	*F*-test	118.95***
F-test all $v_i = 0$	31.67***	*F*-test all $v_i = 0$	28.05***

Notes to the table: (a) The results are calculated by STATA 14.0 software; the command is proposed by Wang (2015). (b) Figures in parentheses are standard error. (c) ***, **, * indicate that the levels of significance are 1%, 5% and 10%, respectively.

pollution discharge fees to the pollution taxes. (2) China's current regulation instruments are relatively one-fold, mainly command and control. However, recent studies support the idea and provide evidence that the key question is not "which instrument is best", but "which mix of instruments is best" (Iraldo et al., 2011). Therefore, Chinese government should pay more efforts to the combination of different types of regulations, such as environmental standards, tradable emissions, pollutant taxes and environmental information disclosure, and then, establish a balanced "environmental regulation mix" system to stimulate a more proactive and strategically based economic response, and to create synergy on firms' competitiveness.

While the reasonable regulation stringency indicates that not the more stringent regulation, the better competitiveness. It must be adapted to firms' capability to withstand increased costs. In order to gain information about firms' capability well and timely, it is necessary for China to conduct general and up-to-date surveys about environmental activities and operation situations in firm level. On the foundation of the latest data and further research, the government will be able to provide reasonable regulation stringency, and to adjust it dynamically in the future.

Acknowledgments

The authors thank the editors and reviewers. We also gratefully acknowledge the help of Professor Andrew N. Kleit from the Pennsylvania State University. This work is funded by the Major Project of National Social Science Fund of China (15ZDA025), and the Doctoral Scientific Fund Project of the Ministry of Education of China (20130041110040).

Appendix A. The SBM Distance Function and Luenberger Productivity Index

A.1. Definition of Environmental Technology

Assume that there are *k* decision-making units (DMUs) at time *t*, and each DMU produces *m* types of desirable outputs ('goods') $y = (y_1, \cdots, y_m) \in R_m^+$, and *i* types of undesirable outputs ('bads') $b = (b_1, \cdots, b_i) \in R_i^+$, by employing *n* types of inputs $x = (x_1, \cdots, x_n) \in R_n^+$. According to Färe et al. (2007), we employ a function to describe the environmental technology as follows:

$$P^t(x^t) = \left\{ \begin{array}{c} \left(y^t, b^t\right) : \sum_{k=1}^{K} \lambda_k^t y_{km}^t \geq y_{km}^t, \forall m; \sum_{k=1}^{K} \lambda_k^t b_{ki}^t = b_{ki}^t, \forall i; \\ \sum_{k=1}^{K} \lambda_k^t x_{kn}^t \leq x_{kn}^t, \forall n; \sum_{k=1}^{K} \lambda_k^t = 1, \lambda_k^t \geq 0, \forall k \end{array} \right\} \tag{A.1}$$

where λ_k^t is the intensity variable. The λ_k^t is weight assigned to each observation when constructing the production possibility frontier. Since the summation of the λ_k^t is 1, variable returns to scale (VRS) are assumed. This technology incorporates null-jointness and weak disposability of outputs.

A.2. A Slacks-based Measure of Directional Distance Functions

Based on the research of Fukuyama and Weber (2009) and Wang et al. (2010), we use a directional slacks-based measure in the estimation of a production frontier. Fukuyama and Weber (2009) point out that slack in the constraints defining the technology suggests that at least one input can be reduced, or one output can be expanded, even though a firm is deemed to be "technically efficient", however, which is often not captured by DDF. The SBM under consideration of undesirable outputs can be defined as:

$$S_V^t\left(x^{t,k'}, y^{t,k'}, b^{t,k'}, g^x, g^y, g^b\right) = \max_{s^x, s^y, s^b} \frac{\frac{1}{N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x} + \frac{1}{M+I}\left[\sum_{m=1}^{M}\frac{s_m^y}{g_m^y} + \sum_{i=1}^{I}\frac{s_i^b}{g_i^b}\right]}{2} \tag{A.2}$$

$$\text{s.t.} \quad \sum_{k=1}^{K} \lambda_k^t x_{kn}^t + s_n^x = x_{k'n}^t, \forall n; \sum_{k=1}^{K} \lambda_k^t y_{km}^t - s_m^y = y_{k'm}^t, \forall m; \sum_{k=1}^{K} \lambda_k^t b_{ki}^t + s_i^b = b_{k'i}^t, \forall i; \lambda_k^t \geq 0, \forall k; s_n^x \geq 0, \forall n; s_m^y \geq 0, \forall m; s_i^b \geq 0, \forall i$$

where S_V^t denotes the SBM with VRS. The vector $(x^{t,k'}, y^{t,k'}, b^{t,k'})$ indicates the *k*'th $DMU_{k'}$'s inputs, good outputs and bad outputs vector at time *t*; (g^x, g^y, g^b) is positive directional vector that contracts inputs and bad outputs, while expands good outputs; (s_n^x, s_m^y, s_i^b) is the slack vector. With the constraint of $(s_n^x, s_m^y, s_i^b) > 0$, it indicates that the actual inputs and bad outputs are larger than their relevant theoretical values, while the actual good outputs are smaller than the theoretical production.

A.3. Luenberger Productivity Index

Environmental TFP is estimated by calculating the Luenberger productivity index for period t and $t+1$ as below:

$$ETFP_t^{t+1} = \frac{1}{2}\left\{\left[S_V^t\left(x^t, y^t, b^t; g\right) - S_V^t(x^{t+1}, y^{t+1}, b^{t+1}; g\right] + \left[S_V^{t+1}\left(x^t, y^t, b^t; g\right) - S_V^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g\right)\right]\right\} \quad (A.3)$$

Furthermore, the Luenberger productivity index can be decomposed into two sources, namely an efficiency change (*Effe*) and a technological progress (*Tech*) as follows:

$$Effe = S_V^t\left(x^t, y^t, b^t; g\right) - S_V^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g\right) \quad (A.4)$$

$$Tech = \frac{1}{2}\left\{\left[S_V^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g\right) - S_V^t(x^{t+1}, y^{t+1}, b^{t+1}; g\right] + \left[S_V^{t+1}\left(x^t, y^t, b^t; g\right) - S_V^t\left(x^t, y^t, b^t; g\right)\right]\right\} \quad (A.5)$$

References

Alpay, E., Buccola, S., Kerkvliet, J., 2002. Productivity growth and environmental regulation in Mexican and U.S. food manufacturing. Am. J. Agric. Econ. 84 (4), 887–901.
Ambec, S., Cohen, M.A., Elgie, S., Lanoie, P., 2013. The Porter Hypothesis at 20: can environmental regulation enhance innovation and competitiveness? Rev. Environ. Econ. Policy 7 (1), 2–22.
Barbera, A.J., McConnell, V.D., 1990. The impact of environmental regulations on industry productivity: direct and indirect effects. J. Environ. Econ. Manag. 18 (1), 50–65.
Berman, E., Bui, L.T.M., 2001. Environmental regulation and productivity: evidence from oil refineries. Rev. Econ. Stat. 83 (3), 498–510.
Boyd, G.A., McClelland, J.D., 1999. The impact of environmental constraints on productivity improvement in integrated paper plants. J. Environ. Econ. Manag. 38 (2), 121–142.
Brännlund, R., Lundgren, T., 2009. Environmental policy without costs? A review of the Porter Hypothesis. Int. Rev. Environ. Resour. Econ. 3 (1), 75–117.
Brunneimer, S., Cohen, M., 2003. Determinants of environmental innovation in US manufacturing industries. J. Environ. Econ. Manag. 45 (2), 278–293.
Chambers, R.G., Färe, R., Grosskopf, S., 1996. Productivity growth in APEC countries. Pac. Econ. Rev. 1 (3), 181–190.
Chen, S.Y., 2010. Green industrial revolution in China: a perspective from the change of environmental total factor productivity. Econ. Res. J. 11, 21–34 (Jing-Ji Yan-Jiu).
Chen, S., Golley, J., 2014. 'green' productivity growth in China's industrial economy. Energy Econ. 44, 89–98.
Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: a directional distance function approach. J. Environ. Manag. 51 (3), 229–240.
Dong, M.J., Li, G., Liang, Y.M., 2012. The sources of China's environmental total factor productivity. J. Quant. Tech. Econ. 2, 3–20 (Shu-Liang Jing-Ji Ji-Shu Jing-Ji Yan-Jiu).
Färe, R., Grosskopf, S., Pasurka, C.A., 2007. Environmental production functions and environmental directional distance functions. Energy 32 (7), 1055–1066.
Franco, C., Marin, G., 2013. The effect of within-sector, upstream and downstream energy taxed on innovation and productivity. FEEM Working Paper. No.103 (2013).
Frondel, M., Horbach, J., Rennings, K., 2007. End-of-pipe or cleaner production? An empirical comparison of environmental innovation decisions across OECD countries. Bus. Strateg. Environ. 16 (8), 571–584.
Fukuyama, H., Weber, W.L., 2009. A directional slacks-based measure of technical inefficiency. Socio Econ. Plan. Sci. 43 (4), 274–287.
Goldar, B., Banerjee, N., 2004. Impact of informal regulation of pollution on water quality in rivers in India. J. Environ. Manag. 73 (2), 117–130.
Golley, J., Meng, X., 2012. Income inequality and carbon dioxide emissions: the case of Chinese urban households. Energy Econ. 34 (6), 1864–1872.
Gray, W.B., Shadbegian, R.J., 2003. Plant vintage, technology, and environmental regulation. J. Environ. Econ. Manag. 46 (3), 384–402.
Greenstone, M., List, J.A., Syverson, C., 2012. The effects of environmental regulation on the competitiveness of US manufacturing. NBER Working Paper No.18392 (September).
Hamamoto, M., 2006. Environmental regulation and the productivity of Japanese manufacturing industries. Resour. Energy Econ. 28 (4), 299–312.
Hansen, B.E., 1999. Threshold effects in non-dynamic panels: estimation, testing, and inference [J]. J. Econ. 93, 345–368.
Hou, Y., Chen, H.Y., 2013. Optimal sewage charges of a three-stage game for the government, polluting firms and the environment firms. Nankai Econ. Stud. 1, 121–128 (Nankai Jing-Ji Yan-Jiu).
Iraldo, F., Testa, F., Melis, M., Frey, M., 2011. A literature review on the links between environmental regulation and competitiveness. Environ. Policy Gov. 21 (3), 210–222.
Jaffe, A.B., Palmer, K., 1997. Environmental regulation and innovation: a panel data study. Rev. Econ. Stat. 79 (4), 610–619.
Jin, B., 2009. Theoretical research on the relationship between the regulation of resources and environment and the industrial competitiveness. China Ind. Econ. 3, 5–17 (Zhong-Guo Gong-Ye Jing-Ji).
Kathuria, V., 2007. Informal regulation of pollution in a developing country: evidence from India. Ecol. Econ. 63 (2–3), 403–417.
Kemp, R., 1997. Environmental Policy and Technical Change: A Comparison of the Technological Impact of Policy Instruments. Edward Elgar, Cheltenham.
Kneller, R., Manderson, E., 2012. Environmental regulations and innovation activity in UK manufacturing industries. Resour. Energy Econ. 34 (2), 211–235.
Koźluk, T., Zipperer, V., 2013. Environmental policies and productivity growth - a critical review of empirical findings. Economics Department Working Papers No. 1096 (November).
Langpap, C., Shimshack, J., 2010. Private citizen suits and public enforcement: substitutes or complements. Environ. Econ. Manag. 59 (3), 235–249.
Lankoski, L., 2010. Linkages between environmental policy and competitiveness. OECD Environment Working Papers, No. 13 (January).
Lanoie, P., Patry, M., Lajeunesse, R., 2008. Environmental regulation and productivity: testing the Porter Hypothesis. J. Prod. Anal. 30, 121–128.
List, J., Catherine, A., Co, Y., 2000. The effects of environmental regulations on foreign direct investment. J. Environ. Econ. Manag. 40 (1), 1–20.
Managi, S., Jena, P.R., 2008. Environmental productivity and Kuznets curve in India. Ecol. Econ. 65 (2), 432–440.
Palmer, K., Oates, W.E., Portney, P.R., 1995. Tightening environmental standards: the benefit-cost or the no-cost paradigm? J. Econ. Perspect. 9 (4), 119–132.
Pargal, S., Wheeler, D., 1996. Informal regulation of industrial pollution in developing countries: evidence from Indonesia. The World Bank Working Paper. No.1416.
Pargal, S., Hettige, H., Singh, M., Wheeler, D., 1997. Formal and informal regulation of industrial pollution: comparative evidence from Indonesia and the United States. World Bank Rev. 11 (3), 433–450.
Peuckert, J., 2014. What shapes the impact of environmental regulation on competitiveness? Evidence from Executive Opinion Surveys. Environ. Innov. Soc. Trans. 10, 77–94.
Porter, M.E., 1991. America's green strategy. Sci. Am. 264 (4), 1–5.
Porter, M.C., van der Linde, 1995. Toward a new conception of the environment-competitiveness relationship. J. Econ. Perspect. 9 (5), 97–118.
Rassier, D.G., Earnhart, D., 2015. Effects of environmental regulation on actual and expected profitability. Ecol. Econ. 112, 129–140.
Rexhäuser, S., Rammer, C., 2014. Environmental innovations and firm profitability: unmasking the Porter Hypothesis. Environ. Resour. Econ. 57 (1), 145–167.
Rubashkina, Y., Galeotti, M., Verdolini, E., 2015. Environmental regulation and competitiveness: empirical evidence on the Porter Hypothesis from European manufacturing sectors. Energ Policy 83, 288–300.
Telle, K., Larsson, J., 2007. Do environmental regulations hamper productivity growth? How accounting for improvements of plants' environmental performance can change the conclusion. Ecol. Econ. 61 (2–3), 438–445.
Wang, Q., 2015. Fixed-effect panel threshold model using Stata [J]. Stata J. 15 (1), 121–134.
Wang, B., Wu, Y.R., Yan, P.F., 2008. Environmental regulation and total factor productivity growth: an empirical study of the APEC economies. Econ. Res. J. 5, 19–32 (Jing-Ji Yan-Jiu).
Wang, B., Wu, Y.R., Yan, P.F., 2010. Environmental efficiency and environmental total factor productivity growth in China's regional economies. Econ. Res. J. 5, 95–109 (Jing-Ji Yan-Jiu).
Watanabe, M., Tanaka, K., 2007. Efficiency analysis of Chinese industry: a directional distance function approach. Energ Policy 35 (12), 6323–6331.
Wu, Y.R., 2008. The role of productivity in China's growth: new estimates. China Econ. Q. 7 (3), 827–842 (Jing-Ji-Xue Ji-Kan).
Yang, C.H., Tseng, Y.H., Chen, C.P., 2012. Environmental regulations, induced R&D, and productivity: evidence from Taiwan's manufacturing industries. Resour. Energy Econ. 34 (4), 514–532.
Zhang, C., Liu, H., Bressers, H.T., Buchanan, K.S., 2011. Productivity growth and environmental regulations - accounting for undesirable outputs: analysis of China's thirty provincial regions using the Malmquist–Luenberger index. Ecol. Econ. 70 (12), 2369–2379.