Journal of Cleaner Production 176 (2018) 895–908

Contents lists available at ScienceDirect

Journal of Cleaner Production

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

Environmental regulation, industrial innovation and green development of Chinese manufacturing: Based on an extended CDM model

Baolong Yuan [a,*], Qiulian Xiang [b]

[a] School of Business, Central South University of Forestry and Technology, Changsha 410004, PR China
[b] School of Business, Central South University, Changsha 410083, PR China

ARTICLE INFO

Article history:
Available online 6 December 2017

Keywords:
Environmental regulation
Industrial innovation
Green total factor productivity
CDM model
Manufacturing industry

ABSTRACT

As for the academics and policymakers, more attention has been given to the issue on how to drive green development of the manufacturing through regulations and innovations. We construct the extended Crépon-Duguet-Mairesse (CDM) model and employ the panel data of Chinese manufacturing industries during 2003–2014 to examine the effects of environmental regulation on industrial innovation and green development. The findings reveal that (1) in the long term, environmental regulation has crowded out R&D investment. (2) Environmental regulation has inhibited patent outputs so that the "weak" version of Porter hypothesis is not underpinned. (3) In the short term, environmental regulation has promoted the improvements of labor productivity, energy efficiency and environmental efficiency in the manufacturing industry excluding green total factor productivity (GTFP), whereas in the long term, environmental regulation only has increased energy efficiency while it has obstructed labor productivity, which provides no support for the "strong" version of Porter hypothesis. (4) Different innovation outputs have distinct influences on labor productivity, energy efficiency, environmental efficiency and GTFP. Finally, this paper provides pertinent policy implications.

© 2017 Elsevier Ltd. All rights reserved.

1. Introduction

The manufacturing sector plays a dominant role in the national economy. However, China's manufacturing is encountering multiple pressures. First of all, the unequilibrium between the supply and demand of energy sources is prominent. In 2016, China's net oil imports reached 378 million tons. The domestic dependence on foreign oil supply increased to 65%. The country's energy consumption was 4.36 billion tons of standard coal, up 34.2% compared to 2010. Secondly, environmental deterioration is exacerbated by a large amount of greenhouse gas emissions. CO_2 emissions reached 7.2 tons per capita in 2011, higher than the world average of 44%. 36% of the world's CO_2 emissions were attributed to the manufacturing industries (Yan and Fang, 2015). In China, the manufacturing industries emitted more than 50% of total CO_2 emissions (Zhao et al., 2014). Lastly, the capability of independent innovation is disadvantaged. Only one company of mainland China was included in the list of Thomson Reuters 2016 Top 100 Global innovators. It is difficult to sustain the development of China's manufacturing sector by increasing factors investment and disregarding ecological environment (Li and Lin, 2016, 2017). Therefore, enhancing the innovation capability of China's manufacturing industries to advance its shift from extensive growth to green development is a pivotal move to realize the medium- and long-term development.

Theoretically, the Porter hypothesis suggests that well-designed environmental regulation can trigger firm's technological innovation that helps gain commercial competitiveness (Porter and van der Linde, 1995). Jaffe and Palmer (1997) present distinct variants of the Porter hypothesis. The "weak" version of the hypothesis posits that environmental regulation will stimulate certain kinds of technological innovation. The "strong" version posits that proper environmental regulation may improve firm's competitiveness. Environmental regulation would push firms to surmount market failures by internalizing the negative externalities generated in the firm's production and operation processes. The key mechanism in this respect is that environmental regulation induces firm

* Corresponding author. School of Business, Central South University of Forestry and Technology, Changsha 410004, PR China.
E-mail addresses: csuft_ybl@163.com (B. Yuan), 1187671447@qq.com (Q. Xiang).

https://doi.org/10.1016/j.jclepro.2017.12.034
0959-6526/© 2017 Elsevier Ltd. All rights reserved.

innovation to reduce its compliance cost. The innovation effect, making production processes and products more efficient, the cost savings of which that can be achieved are sufficient to overcompensate for the compliance cost. In this regard, environmental regulation is thus advertised as a “win-win” strategy, leading to better environmental quality and higher firm's productivity (Rubashkina et al., 2015).

The extant research conclusions regarding the relationship between environmental regulation and R&D investment are mixed. The link between them varies in different countries and industries. Jaffe and Palmer (1997), Brunneimer and Cohen (2003), and Gray and Shadbegian (2003) found that the relationship between environmental regulation and R&D expenditures of the US manufacturing is positive. Hamamoto (2006) concluded that environmental regulation plays a positive role in R&D expenditures of Japanese manufacturing. Yang et al. (2012) discovered that environmental regulation is positively related to Taiwan's industrial R&D investments. Chakraborty and Chatterjee (2017) maintained that environmental regulation can promote the increase in innovation expenditures of Indian leather and textile industries. Costa-Campi et al. (2017) confirmed the galvanizing effect of environmental regulation intensity on firm's R&D investments. On the contrary, Kneller and Manderson (2012) demonstrated that environmental regulation could not help increase R&D investments of Britain manufacturing. Rubashkina et al. (2015) found that current environmental regulation has an insignificant crowding-out effect on R&D investments. Therefore, most of prior studies use a single indicator such as R&D investments, patents, etc. to measure the level of innovation and the innovation process is not dissected further. Moreover, the problem that under the external environmental regulation, the industry will respond to or comply with environmental regulation through what kind of innovation is not addressed.

To date, the literature on the relationship between innovation input and innovation output is controversial. An array of literature deems innovation input as a critical driver of innovation output. Using the panel data of Argentine manufacturing, Chudnovsky et al. (2006) found that firm's in-house R&D expenditures have positive payoffs in terms of enhanced probability of introducing new products and/or processes to the market. Marchi (2012) employed the data from the Community Innovation Survey (CIS) on Spanish manufacturing firms and suggested that firm's R&D cooperation with external partners can stimulate environmental innovation. Hashi and Stojčič (2013) contended that R&D intensity is able to significantly promote sales from new products. Costa-Campi et al. (2014) used the data taken from the Technological Innovation Panel (PITEC) for Spanish firms and found that R&D intensity of the energy industry is positively related to process innovation. Song and Oh (2015) analyzed the Korea Innovation Survey 2008 data and demonstrated that R&D intensity has a strong and positive effect on process innovation in the energy intensive industry. Acosta et al. (2015) adopted a sample of Spanish firms in the food and beverage industry and pointed out the significant role of R&D expenditure for product and organizational innovation. Raymond et al. (2015) employed the panel data of Dutch and French manufacturing firms. The results provide evidence of robust unidirectional causality from R&D to firm innovation. Frank et al. (2016) used the data from Brazilian industrial sectors and revealed that market-oriented innovation input shows a positive effect on innovation output.

However, a fraction of studies contend that there is no positive relationship between innovation input and innovation output. Benavente (2002) studied the firms in Chile manufacturing industry and found that firm's innovation is not significantly influenced by R&D investments in the short run. Ghisetti and Pontoni (2015) also discovered that R&D investment does not have a significant effect on environmental innovation. Acosta et al. (2015) manifested that R&D expenditure can not significantly promote firm's process innovation. Frank et al. (2016) suggested that a technology-acquisition strategy of innovation input generates negative results on innovation output of firms. In summary, first, substantial studies have used the data of enterprises from developed countries and areas such as the US, Germany, the European countries, etc. (Kesidou and Demirel, 2012; Horbach et al., 2012; Baumann and Kritikos, 2016; Albrizio et al., 2017). Conversely, a paucity of research deals with the impact of environmental regulation on innovation process of the manufacturing industry in China, the largest developing country. Second, these studies focus on the objective goal of innovation, i.e. the realization of product innovation, process innovation, organizational innovation and marketing innovation (Hashi and Stojčič, 2013; Costa-Campi et al., 2014; Marin, 2014; Acosta et al., 2015; Baumann and Kritikos, 2016). Specifically, they make great efforts to examine the direct effect of innovation inputs but they do not capture the impact of environmental regulation, this institutional factor, on industrial innovation behavior. In addition, a body of literature maintains that sometimes industrial innovation measured by the number of patents may be strategic behaviors (Dosi et al., 2006; Hall and Harhoff, 2012; Li and Zheng, 2016). Thus, to respond to the government's environmental regulation, do different innovation behaviors occur in China's manufacturing industries? If so, do these diverse innovations have heterogeneous effects on industrial green development? These questions deserve to be investigated further.

Two strands of literature focuses on innovation output and innovation performance. First, innovation can directly promote the improvement of productivity or financial performance. Baumann and Kritikos (2016) argued that a significant and positive correlation exists between firm innovation and productivity. Gilli et al. (2014), Przychodzen and Przychodzen (2015) and Lee and Min (2015) found that innovation is capable of significantly improving firm's financial performance. Ghisetti and Rennings (2014) confirmed that energy and resource efficient innovations positively affect firms' competitiveness. Guo et al. (2016) found that energy technology innovation can promote the transition of coal-based economy. Ramanathan et al. (2017) used nine case studies of UK and Chinese firms. The results show that firms that adopt a more dynamic approach to respond to environmental regulations innovatively are generally better able to reap the private benefits of sustainability. Second, it is contingent whether innovation can promote economic performance of an industry. Amores-Salvadó et al. (2014) found that environmental product innovation does not have a statistically significant effect on firm performance. However, environmental product innovation and the green corporate image can interact and promote firm performance. Amores-Salvadó et al. (2015) demonstrated that environmental management systems positively moderate the relationship between environmental product innovation and firm market performance. Kim et al. (2016) believed that, under high uncertainty, the later the timing of the patent, the higher the innovation performance, while under low uncertainty, there is an early-mover advantage. It is noted that economic indicators such as financial performance, productivity, total factor productivity (TFP), etc. are extensively applied to measure industrial innovation performance in a plethora of literature while they fail to mirror the interacted but different impacts of environmental regulation and innovation outputs on economy, energy and environment.

To overcome the above deficiencies, this paper has made following contributions to knowledge. First, this study explores the effects of environmental regulation on the inputs and outputs of industrial innovation by employing the extended CDM (Crépon et al., 1998) model. Consequently, we open the black box of innovation mentioned in the Porter hypothesis and explain why the conclusions on the Porter hypothesis are conflicting. Second, this paper, for the first time, divides innovation outputs into patent outputs and value outputs in light of innovation transformation. According to innovation motive, we subdivide patent outputs into invention patents and non-invention patents, where invention patents represent the outputs of substantial innovation and non-invention patents stand for the outputs of strategic innovation. By studying the impacts of environmental regulation on different innovation outputs of the manufacturing industry, we reveal that innovation behaviors of China's manufacturing industries vary in response to institutional pressure, i.e. environmental regulation, which is of theoretical importance to the extension of the "weak" version of Porter hypothesis. Third, given the realistic demand for the coordinated development of economy, energy and environment in China's manufacturing sector, GTFP is used as a proxy for the green development of manufacturing industry and thus we avoid an overestimate on the productivity by not merely using economic indicators for measuring it. More importantly, we also examine the performance difference between substantive innovation and strategic innovation from the perspective of innovation motive. Therefore, this study enriches the "strong" version of Porter hypothesis. Besides, it is also conducive to ascertain whether there is a synergy between Chinese environmental regulations, thus providing empirical evidence for the Chinese government to utilize policy portfolios to push forward green development of the manufacturing industry. Fourth, taking the panel data of Chinese manufacturing industries as the sample, this paper studies the impact of environmental regulation on innovation process of the manufacturing industry, which complements the existing literature. Hence, this study provides policy implications not only for China but also for other developing countries to promote industrial green development via environmental regulation.

By constructing the extended CDM model and using the panel data of Chinese manufacturing in 2003–2014, we classify innovation outputs into three types, namely invention patents, non-invention patents and sales from new products, green development of the manufacturing industry into three dimensions, namely labor productivity, energy efficiency and environmental efficiency, and burrow into the relationships between environmental regulation, industrial innovation and green development. The remainder of the paper is structured as follows. Section 2 contains material and methods. Empirical results and discussion are presented in Section 3. And Section 4 shows the conclusions.

2. Material and methods

2.1. Data source and processing

For the convenience of statistical analysis of the data, based on the division standard of national economic industries (GB/T 4754–2011) and the industry categorizations of *China Statistical Yearbook*, *China Statistical Yearbook on Environment*, *China Statistical Yearbook on Science and Technology* and *China Energy Statistical Yearbook*, we divide China's manufacturing sector into 28 subsectors (Table A.1).

The definitions of all variables are described in Table 1. R&D investment, the number of patents, the number of invention patents, sales from new products, government subsidy, the quality of labor force and the number of the R&D institution are collected from *China Statistical Yearbook on Science and Technology* (2003–2014). The data, energy consumption in each industry, comes from *China Energy Statistical Yearbook* (2003–2014). Discharge amount of waste water, COD emission, waste gas emission, SO_2 emission, soot and dust emission, discharge amount of solid waste, and operating cost of treatment facilities for industrial pollution are from *China Statistical Yearbook on Environment* (2003–2014). CO_2 emission is calculated according to the method mentioned in IPCC (Intergovernmental Panel on Climate Change) Guidelines for National Greenhouse Gas Inventories (Ren et al., 2014; Prasad and Mishra, 2017). The data, including capital input, labor input, total output value, FDI, market competition, capital intensity and ownership type, is obtained from *China Statistical Yearbook* (2003–2014) and *China Industry Statistical Yearbook* (2003–2014).

Energy efficiency, environmental efficiency and GTFP are calculated by the SE-DEA model (Yuan et al., 2017; Li and Lin, 2017), as shown in Eq. (A.1). The input indicators for measuring energy efficiency include comprehensive energy consumption, capital input, labor input and the output indicator is total output value of the industry (Lin and Zheng, 2017). Regarding environmental efficiency, the input indicators include waste water, waste gas, COD, SO_2, soot and dust, solid waste and CO_2 and the output indicator is

Table 1
The definitions of all variables in the econometric regression models.

Variable	Definition	Unit
R&D intensity (R&D)	R&D investment of the industry per capita	Yuan/Person
Invention patents (PAT)	The number of invention patents of the industry	Piece
Non-invention patents (NPAT)	The industry's total number of patent applications minus the number of invention patents	Piece
Sales from new products (NEW)	Sales from new products of the industry	10,000 Yuan
Labor productivity (LP)	Industrial output value per capita	10,000 Yuan/Person
Energy efficiency (ENE)	Calculated by SE-DEA model	–
Environmental efficiency (ENV)	Calculated by SE-DEA model	–
Green total factor productivity (GTFP)	Calculated by SE-DEA model	–
Environmental regulation (ER)	Operating cost of pollution treatment facilities of the industry	10,000 Yuan
Government subsidy (SUB)	Government funds for scientific and technological activities	10,000 Yuan
Foreign direct investment (FDI)	Investments from large- and medium-sized foreign-funded enterprises, or Hong Kong, Macao and Taiwan	10,000 Yuan
Market competition (MC)	The difference of newcomers between the current period and the previous period	Unit
Capital intensity (CI)	Fixed assets/Total assets of the industry	%
Ownership type (OWN)	Ratio of output value of the state-owned and state-holding enterprises to total output value of the industry	%
Industry size (GDP)	Total output value of the industry	100 million Yuan
The quality of labor force (LAB)	The proportion of people with master's or doctorate degrees in the R&D institution	%
R&D institution (TI)	The number of R&D institutions in enterprises	Unit

total output value of the industry (Zhang et al., 2015). For GTFP, the input indicators include comprehensive energy consumption, capital input and labor input. The undesirable outputs include waste water, waste gas, COD, SO_2, soot and dust, solid waste and CO_2. The desirable output denotes total output value of the industry (Li and Wu, 2017; Yuan et al., 2017). To eliminate the impact of inflation, we use current price/PPI (Producer's Price Index for Manufactured Products) to transform current year's prices (current data) into constant price of 2002. Investment in fixed assets of each industry is computed with Perpetual Inventory Method (Lin and Zhao, 2016; Meng et al., 2016). See the results in Figs. A.1-A.3. Table 2 summarizes the descriptive statistics of all variables in the econometric models.

2.2. Methodology

2.2.1. Classical CDM model

The classical CDM model can unravel the black box of innovation process, identify the determinants of innovation input and the relationships between innovation input and innovation output, innovation output and innovation performance (Crépon et al., 1998). The model consists of three steps. In the first step, we analyze whether firms decide to undertake R&D projects or not and the amount of resources to devote to R&D activities. In the second step, we explore the effect of firm R&D inputs and other resources on innovation outputs. In the third step, the impact of firm innovation output on productivity is assessed (Mairesse et al., 2005; Marin, 2014). Therefore, the model comprises the R&D function, the innovation function and the production function. We extend R&D equation, innovation equation and productivity equation and examine the effects of environmental regulation on innovation input, innovation output and innovation performance.

2.2.2. Extended CDM model

2.2.2.1. R&D equation. Excluding the R&D input decision function, we merely study the R&D intensity function for every industry in China's manufacturing sector having R&D inputs (Marin, 2014; Baumann and Kritikos, 2016). The R&D intensity function aims at identifying the determinants of industrial R&D intensity (Marin, 2014). Because the efficacy of R&D investments is lagged to a certain extent and previous R&D investments can affect current investments, one lag of R&D is introduced to investigate the dynamic effect of R&D equation (Kneller and Manderson, 2012).

The Porter hypothesis postulates that well-crafted environmental regulation can encourage firms to carry out technological innovation. The innovation effect is sufficient to offset or even exceed the compliance cost attributed to environmental regulation (Porter and van der Linde, 1995). Hence, environmental regulation is an important driver of the manufacturing industry investing innovation activities. We use operating cost of pollution treatment facilities for industrial pollution to measure the intensity of environmental regulation (Rubashkina et al., 2015). The higher the operating cost of pollution treatment facilities for industrial pollution, the greater the intensity of environmental regulation in the manufacturing industry. Owing to the payback period, this proxy may have a lagged effect on R&D intensity. To capture this lagged effect, one lag of environmental regulation is regarded as a key independent variable (Rubashkina et al., 2015; Zhao and Sun, 2016; Ren et al., 2016; Wang and Shen, 2016).

Drawing on the research of Horbach (2008) and Marin (2014), we choose control variables from three aspects: supply side (technology push), demand side (market pull) and industry characteristics. The factors of technology push contains government subsidy (Horbach, 2008) and foreign direct investment (Yuan et al., 2017). Considering the uncertainties and risks of innovation, incentives for the industry to engage in innovation are inadequate when only relying on industrial R&D investment. Consequently, the government's financial subsidies for innovation can complement R&D investments of an industry so as to propel industrial innovation. The role of FDI in promoting the development of Chinese manufacturing industries is crucial since foreign investment may mitigate environmental damage through the transfer of clean technologies. Market competition (Kneller and Manderson, 2012), belonging to the factor of market pull, is likely to compel the manufacturing industries to launch innovation thus to enhance their competitiveness. With respect to industry characteristics, we select capital intensity (Chang et al., 2013), ownership (Li and Lin, 2016) and industry size (Kneller and Manderson, 2012). The capital-intensive industry lays more emphasis on R&D investment compared with the labor-intensive industry. Furthermore, the funds for R&D of the state-owned manufacturing companies are much more abundant than that of the private companies. Therefore, R&D intensity of the industry is more likely to be intensified along with the increase in the proportion of output value of the state-owned companies to total output value of the industry. Moreover, industry size is also a determinant of R&D intensity, that is, the larger the industry size, the more the R&D investment of the industry. R&D equation is shown as Eq. (1):

$$R\&D_{i,t} = \alpha_0 + \alpha_1 R\&D_{i,t-1} + \alpha_2 ER_{i,t} + \alpha_3 ER_{i,t-1} + \alpha_4 Control_{i,t} + \varepsilon_{i,t} \tag{1}$$

where the explained variable, $R\&D_{i,t}$, stands for R&D intensity of an industry. The explanatory variable, $R\&D_{i,t-1}$ is one lag of R&D intensity. $ER_{i,t}$ means environmental regulation and correspondingly, $ER_{i,t-1}$ means one lag of environmental regulation. $Control_{i,t}$ denotes control variables, including government subsidy (*SUB*), foreign direct investment (*FDI*), market competition (*MC*), capital intensity (*CI*), ownership type (*OWN*), industry size (*GDP*). ε is a random error. i represents the industry. t denotes the year. Variables are defined in Table 1.

2.2.2.2. Innovation equation. The innovation equation, known as a patent function or a sales from new products function, aims to examine the effects of R&D investment of an industry and other factors on innovation output. We construct a patent function (patent output) and a sales from new products function (value output) respectively to further investigate the different effects of environmental regulation and innovation input on various types of

Table 2
The descriptive statistics of variables.

Variable	Mean	Max	Min	Std. dev.	Observations
R&D	8.657	10.950	5.814	1.204	336
PAT	1.210	4.202	−3.470	1.497	336
NPAT	2.153	4.710	−1.758	1.268	336
NEW	15.898	19.402	11.661	1.533	336
LP	1.357	1.807	0.780	0.207	336
ENE	−1.200	0.316	−2.919	0.596	336
ENV	−2.103	0.799	−5.116	1.319	336
GTFP	−1.337	0.662	−3.576	0.951	336
ER	11.293	15.388	7.005	1.779	336
SUB	9.859	14.110	5.135	1.895	336
FDI	−2.182	−1.192	−8.651	0.990	336
MC	7.183	11.761	0.693	2.069	336
CI	−0.764	−0.064	−1.422	0.229	336
OWN	−2.259	−0.005	−5.816	1.181	336
GDP	9.250	11.359	6.534	1.073	336
LAB	−2.612	−1.091	−4.873	0.636	336
TI	5.920	8.753	3.258	1.277	336

patents (Sun et al., 2008) and uncover the impact of innovation motivation on green development of the manufacturing industry. The patent equation is classified into an equation of invention patents and an equation of non-invention patents wherein invention patents represent the substantial innovation and non-invention patents stand for the strategic innovation (Li and Zheng, 2016). Given that the output of patents may lag behind current R&D investment (Hall et al., 1986), one lag of R&D intensity is used as the independent variable. Current environmental regulation and one lag of environmental regulation are both taken as key independent variables as well. Additionally, building on Eq. (1), the quality of labor force and the number of R&D institutions are added as control variables. The innovation equation is exhibited as Eq. (2).

$$\begin{cases} PAT_{i,t} = \beta_0 + \beta_1 R\&D_{i,t} + \beta_2 R\&D_{i,t-1} + \beta_3 ER_{i,t} + \beta_4 ER_{i,t-1} + \beta_5 Control_{i,t} + \varepsilon_{i,t} \\ NPAT_{i,t} = \phi_0 + \phi_1 R\&D_{i,t} + \phi_2 R\&D_{i,t-1} + \phi_3 ER_{i,t} + \phi_4 ER_{i,t-1} + \phi_5 Control_{i,t} + \varepsilon_{i,t} \\ NEW_{i,t} = \delta_0 + \delta_1 R\&D_{i,t} + \delta_2 R\&D_{i,t-1} + \delta_3 ER_{i,t} + \delta_4 ER_{i,t-1} + \delta_5 Control_{i,t} + \varepsilon_{i,t} \end{cases} \tag{2}$$

where the explained variables, viz. $PAT_{i,t}$, $NPAT_{i,t}$, $NEW_{i,t}$, denote the output of invention patents, the output of non-invention patents and sales from new products at the industry level respectively. The explanatory variables, $R\&D_{i,t}$, $R\&D_{i,t-1}$, $ER_{i,t}$, $ER_{i,t-1}$, are defined as same as Eq. (1). $Control_{i,t}$ represents control variables, including the quality of labor force (*LAB*), the number of R&D institutions (*TI*), government subsidy (*SUB*), foreign direct investment (*FDI*), market competition (*MC*), capital intensity (*CI*), ownership type (*OWN*) and industry size (*GDP*).ε is a random error term. The definitions of variables are displayed in Table 1.

2.2.2.3. Productivity equation. The productivity equation is designed to examine the effects of patents and sales from new products on productivity. Labor productivity is used as the dependent variable in the productivity equation of the classical CDM model, whereas energy consumption and environmental pollution in the development of the manufacturing industry are not taken into account, which may overestimate labor productivity (Zhang et al., 2011; Chen and Golley, 2014). Therefore, considering the realistic need of the coordinated development of economy, energy and environment of China's manufacturing and the ultimate goal of realizing “strong” Porter hypothesis, we use GTFP to measure the level of green development of China's manufacturing industry (Chen and Golley, 2014). China performs well on the economic front, while the energy and environmental problems are still not eradicated (Wang and Feng, 2015). To explore the effects of environmental regulation and innovation output on energy and environmental performances of the manufacturing industry, energy efficiency and environmental efficiency are introduced as the explained variables to capture the different effects and identify whether there is a synergy between environmental regulations. Meanwhile, we include lagged explained variables to investigate the dynamic effects (Chen and Golley, 2014). Invention patents (*PAT*), non-invention patents (*NPAT*) and sales from new products (*NEW*) in Eq. (2) are regarded as the explanatory variables in the productivity equation. Current environmental regulation and one lag of environmental regulation are taken as key independent variables. Because total industrial output value is used to measure the dependent variable, excluding industry size, the control variables are almost identical with Eq. (1). The productivity equation is presented as Eq. (3).

$$\begin{cases} LP_{i,t} = \gamma_0 + \gamma_1 LP_{i,t-1} + \gamma_2 PAT_{i,t} + \gamma_3 NPAT_{i,t} + \gamma_4 NEW_{i,t} + \gamma_5 ER_{i,t} + \gamma_6 ER_{i,t-1} + \gamma_7 Control_{i,t} + \varepsilon_{i,t} \\ ENE_{i,t} = \theta_0 + \theta_1 ENE_{i,t-1} + \theta_2 PAT_{i,t} + \theta_3 NPAT_{i,t} + \theta_4 NEW_{i,t} + \theta_5 ER_{i,t} + \theta_6 ER_{i,t-1} + \theta_7 Control_{i,t} + \varepsilon_{i,t} \\ ENV_{i,t} = \kappa_0 + \kappa_1 ENV_{i,t-1} + \kappa_2 PAT_{i,t} + \kappa_3 NPAT_{i,t} + \kappa_4 NEW_{i,t} + \kappa_5 ER_{i,t} + \kappa_6 ER_{i,t-1} + \kappa_7 Control_{i,t} + \varepsilon_{i,t} \\ GTFP_{i,t} = \lambda_0 + \lambda_1 TFP_{i,t-1} + \lambda_2 PAT_{i,t} + \lambda_3 NPAT_{i,t} + \lambda_4 NEW_{i,t} + \lambda_5 ER_{i,t} + \lambda_6 ER_{i,t-1} + \lambda_7 Control_{i,t} + \varepsilon_{i,t} \end{cases} \tag{3}$$

where the explained variables, i.e. $LP_{i,t}$, $ENE_{i,t}$, $ENV_{i,t}$, $GTFP_{i,t}$ denote labor productivity, energy efficiency, environmental efficiency, GTFP of an industry respectively. The explanatory variables, i.e. $LP_{i,t-1}$, $ENE_{i,t-1}$, $ENV_{i,t-1}$, $GTFP_{i,t-1}$ denote the lagged explained variables. The definitions of $PAT_{i,t}$, $NPAT_{i,t}$, $NEW_{i,t}$, $ER_{i,t}$ and $ER_{i,t-1}$ are in line with Eq. (2). $Control_{i,t}$ represent the control variables, including government subsidy (*SUB*), foreign direct investment (*FDI*), market competition (*MC*), capital intensity (*CI*) and ownership type (*OWN*).ε is the random error term. The definitions of all variables are described in Table 1.

3. Empirical results and discussion

3.1. Stationary test and cointergration test

We conduct stationary test on the data before the econometric regression analysis. In this paper, we employ the LLC (Levin-Lin-Chu), IPS (Im-Pesaran-Shin), Fisher-ADF and Fisher-PP test to determine the stability of variables, and also ensure the robustness of the test. Among them, the LLC test is a method with the same unit root, however, the IPS, Fisher-ADF and Fisher-PP are the test methods with different unit root. The null hypothesis of four tests are the unit root. Unit root test equation include the constants and time trends. The results showed that the first order differential sequence of all variables are stationary (see Table 3).

Table 3
The results of unit root test.

Series	LLC	IPS	Fisher-ADF	Fisher-PP	Result
$\Delta R\&D$	-11.21^{***}	-5.42^{***}	5.33^{***}	3.71^{***}	stationary
ΔPAT	-9.13^{***}	-5.38^{***}	4.56^{***}	12.73^{***}	stationary
$\Delta NPAT$	-8.24^{***}	-5.22^{***}	4.13^{***}	9.78^{***}	stationary
ΔNEW	-2.85^{***}	-5.69^{***}	4.69^{***}	3.51^{***}	stationary
ΔLP	-13.22^{***}	-4.30^{***}	10.92^{***}	9.99^{***}	stationary
ΔENE	-4.64^{***}	-3.26^{***}	3.06^{***}	3.45^{***}	stationary
ΔENV	-9.08^{***}	-2.80^{***}	7.44^{***}	6.69^{***}	stationary
$\Delta GTFP$	-2.26^{***}	-1.60^{*}	5.39^{***}	4.89^{***}	stationary
ΔER	-4.30^{***}	-6.98^{***}	2.82^{***}	10.66^{***}	stationary
ΔSUB	-11.63^{***}	-6.15^{***}	11.34^{***}	5.35^{***}	stationary
ΔMC	-8.83^{***}	-6.30^{***}	4.03^{***}	2.52^{***}	stationary
ΔFDI	-26.41^{***}	-3.66^{***}	50.58^{***}	69.89^{***}	stationary
ΔCI	-21.53^{***}	-10.14^{***}	62.86^{***}	82.41^{***}	stationary
ΔOWN	-13.89^{***}	-4.46^{***}	5.78^{***}	11.59^{***}	stationary
ΔGDP	-7.50^{***}	-7.15^{**}	2.66^{***}	5.04^{***}	stationary
ΔLAB	-14.26^{***}	-9.86^{***}	6.94^{***}	130.49^{***}	stationary
ΔTI	-9.18^{***}	-1.90^{**}	5.76^{***}	106.84^{***}	stationary

Note: ***,**, and * indicate significance at the 1, 5, and 10% levels, respectively.

To address the spurious regression phenomenon, a cointegration analysis of variables in Eqs. (1)–(3) must be undertaken prior to estimating the parameters of panel data. We perform the cointegration test proposed by Kao (1999). The results show that the panel cointegration relationships reside between dependent variables and independent variables of Eqs. (1)–(3) (see Table 4).

3.2. R&D intensity

Table 5 presents the estimated results on the effect of environmental regulation on R&D intensity of the manufacturing industry in Eq. (1). Models 1–4 report the results of pooled estimation, fixed effect estimation, two-step SYS-GMM. Because industrial innovation may reversely affect environmental regulation, it is necessary to detect the endogeneity of environmental regulation. χ^2 (1) of Hausman test is 1.02 ($p = 0.31$), indicating that environmental regulation is isolated from the endogeneity problem. Moreover, χ^2 (1) of DWH test is 1.33 ($p = 0.25$), which further evidences the conclusion. χ^2 (1) of White Heteroscedasticity Test is 70.06 ($p < 0.1$) and the homoscedasticity hypothesis is rejected. Meanwhile, χ^2 (1) of BP test is 27.86 ($p < 0.01$), further showing that in the model, the heteroscedasticity exists. To remove the heteroscedasticity, we take the log of all variables and adopt the robust standard deviation to obtain t-value or z-value when taking regression analysis. Current environmental regulation and lagged environmental regulation are made regression analysis respectively to avoid the multicollinearity.

The consistency of dynamic panel SYS-GMM estimation requires uncorrelated second-order difference residuals. The results of Models 3 and 4 show that the null hypothesis is rejected by AR (1) but accepted by AR (2). The AR (2) is not significant, which confirms that second-order residuals are irrelevant and the null hypothesis is supported. At the same time, the Sargan tests of Models 3 and 4 support the null hypothesis, demonstrating that overidentifying restrictions of instrumental variables are invalid. The SYS-GMM estimators are consistent. But if the instrumental variable used is weak, dynamic panel SYS-GMM estimators may be biased. Bond (2002) put forward a criterion to identify this scenario, that is, the good estimator of lagged dependent variable should be in the range of mixed regression estimator to fixed effect regression estimator. As we expected, SYS-GMM estimators of lagged dependent variables in Models 3 and 4 exactly satisfy the criterion.

In Model 3, the coefficient of $R\&D_{t-1}$ is 0.494 ($p < 0.01$), which predicts that if previous R&D intensity increases by 1%, current R&D intensity will increase by 0.494%. Environmental regulation is negatively but insignificantly associated with R&D intensity of the manufacturing industry, indicating that the crowding out effect of environmental regulation on R&D investment is not evident. The result coincides with the research of Rubashkina et al. (2015), who chose the European manufacturing industry as the sample and found that current environmental regulation has an insignificantly

Table 4
Kao cointegration test.

	Eq (1) (R&D)	Eq (2) (PAT)	Eq (2) (NPAT)	Eq (2) (NEW)	Eq (3) (LP)	Eq (3) (ENE)	Eq (3) (ENV)	Eq(3) (GTFP)
ADF statistic	−4.642	−5.625	−10.019	−10.316	−8.281	−1.411	−1.602	−1.697
P-value	0.000	0.000	0.000	0.000	0.000	0.079	0.055	0.045

Table 5
Regression results of the R&D equation.

Variable	Model 1 (Pooled OLS)	Model 2 (FE)	Model 3 (SYS-GMM)	Model 4 (SYS-GMM)
$R\&D_{t-1}$	0.925^{***}(39.67)	0.447^{***}(6.25)	0.494^{***}(13.91)	0.505^{***}(16.54)
ER	−0.011 (-1.20)	−0.012 (-0.66)	−0.021 (-0.94)	
ER_{t-1}				-0.099^{***}(-9.99)
SUB	0.017 (1.12)	0.045^{*}(1.72)	0.023 (1.13)	0.009 (0.39)
FDI	-0.040^{*}(-1.90)	0.077 (1.07)	-0.379^{***}(-4.82)	-0.351^{***}(-4.49)
MC	0.021^{***}(3.53)	0.045^{***}(4.44)	0.112^{***}(16.32)	0.098^{***}(14.17)
CI	0.049 (0.67)	0.201 (1.24)	−0.446 (-1.61)	−0.362 (-1.55)
OWN	0.024 (1.14)	0.096^{**}(2.09)	0.208^{***}(6.00)	0.234^{***}(6.05)
GDP	0.022 (0.82)	0.3222^{***}(5.91)	0.159^{***}(4.26)	0.223^{***}(6.92)
Cons	0.336^{**}(2.48)	1.751^{***}(3.54)	2.213^{***}(5.49)	2.868^{***}(8.23)
R^2	0.956	0.789		
F-value	4889.66 [0.00]	111.62 [0.00]		
AR (1)			−3.287 [0.00]	−3.571 [0.00]
AR (2)			0.101 [0.92]	0.122 [0.90]
Sargan χ^2			26.336 [0.98]	25.19 [0.99]
Wald χ^2			4273.80 [0.00]	3986.54 [0.00]
Observations	336	336	252	252

Note: The t-statistic or z-statistic are in parentheses. P-value is in square brackets. ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively.

crowding-out effect on R&D investment after considering the endogeneity. However, it conflicts with the following studies. Porter and van der Linde (1995) discovered that environmental regulation can promote R&D investment. Based on the sample of British manufacturing industry, Kneller and Manderson (2012) revealed that environmental regulation can significantly inhibit R&D. However, in Model 4, when lagged environmental regulation is introduced, we find that it can significantly weaken R&D intensity of the manufacturing industry, proving that environmental regulation has a lagged effect on R&D intensity and in the long term, it will significantly crowd out R&D investment. Still, this result is consistent with Rubashkina et al. (2015). On the contrary, it is not in accordance with the conclusions of Jaffe and Palmer (1997), Brunneimer and Cohen (2003), Gray and Shadbegian (2003), Hamamoto (2006), Yang et al. (2012). They argued that stronger environmental regulation can stimulate enterprises to increase R&D investment. The primary reason for the aforementioned conclusions is the development of China's manufacturing industry has formed the path dependence on the inputs of resources and energy, i.e. the investment-driven development. In this context, the industry has relatively weak innovation-driven capability and low R&D investment. Under the double constraints of environmental regulation pressure and dispirited innovation enthusiasm, corporations have to increase the curtailment of R&D investment and purchase the equipment for energy conservation and emission reduction to comply with government environmental regulation.

3.3. Innovation outputs

Table 6 lays out the estimated results of Eq. (2). Given that the dependent variable in Models 5–8 is the number of patents, a nonnegative integer, we use a negative binomial (NB2) regression model (Marin, 2014). The α-values of Models 5–8 are at the 95% confidence interval. As a result, at 5% significance level, the null hypothesis that the overdispersion parameter α is equal to 0 is rejected and Negative Binomial (NB2) regression model is applicable. We employ Hausman test to make a choice between fixed effect model and random effect model before estimating Models 9 and 10 and the results show that fixed effect model should be chosen.

Models 5 and 6 present the estimated results on the effects of environmental regulation and R&D intensity on invention patents of the manufacturing industry. The coefficient of ER is −0.191 ($p < 0.01$), which shows that environmental regulation significantly hinders invention patents and so does lagged environmental regulation. Li and Wu (2017) propped up this result and also found that environmental regulation has stifled original innovation at the region level, as opposed to the research of Rubashkina et al. (2015), who believed that lagged environmental regulation has a significantly positive effect on patent outputs of the manufacturing industry. One possible explanation is that in R&D equation, environmental regulation crowds out R&D investment, which in the second stage, gravely suppresses the outputs of invention patents. The coefficient of R&D is 0.314 ($p < 0.01$), meaning that R&D intensity is vital to boost industrial invention patents, in accordance with the conclusions of Acosta et al. (2015), Marchi (2012), Costa-Campi et al. (2014), Song and Oh (2015). In the meantime, lagged R&D intensity notably promotes invention patents, the effect degree of which is the same with current R&D intensity, showing that the effect of R&D investment features obvious hysteresis and consecutiveness.

Models 7 and 8 show the estimated results on the effects of environmental regulation and R&D intensity on non-invention patents of the manufacturing industry. The coefficient of ER is −0.181 ($p < 0.01$), demonstrating that environmental regulation plays a significant role in depressing non-invention patents and so does lagged environmental regulation. It is attributable to the crowding out effect of environmental regulation on R&D investment of the manufacturing industry and the outputs of non-invention patents are limited. The regression coefficient of R&D is 0.125 ($p < 0.1$), indicating that R&D intensity promotes industrial non-invention patents. But in contrast to Model 5, the elasticity of R&D intensity on non-invention patents is lower. The impact of lagged R&D intensity on non-invention patents is not evident since non-invention patents comprise design patents and utility patents. The input-output cycle of R&D for these types of patents is relatively short. Specifically, it takes short time for R&D investment to be transformed into design and utility patents. However, with

Table 6
Regression results of the innovation equation.

Variable	Patents output				Value output	
	Invention patents (PAT)		Non-invention patents (NPAT)		Sales from new products (NEW)	
	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
ER	−0.191***(-6.48)		−0.181***(-4.78)		0.011 (0.64)	
R&D	0.314***(5.15)		0.125*(1.82)		0.452***(10.51)	
ER_{t-1}		−0.173***(-5.68)		−0.186***(-5.35)		−0.029 (-1.61)
$R\&D_{t-1}$		0.294***(4.41)		0.046 (0.73)		0.217***(4.24)
LAB	0.452***(6.06)	0.437***(5.65)	−0.064 (-0.93)	−0.073 (-1.07)	−0.011 (-0.38)	0.061 (1.16)
TI	0.485***(5.65)	0.556***(6.71)	0.452***(4.27)	0.509***(5.48)	0.004 (0.12)	0.095**(2.50)
SUB	0.320***(6.32)	0.292***(5.65)	0.268***(4.24)	0.271***(4.62)	0.008 (0.30)	0.028 (0.96)
FDI	−0.104*(-1.87)	−0.105*(-1.83)	−0.151**(-2.55)	−0.175***(-3.03)	−0.215***(-4.66)	−0.147***(-2.65)
MC	0.010 (0.48)	0.006 (0.32)	−0.023 (-1.19)	−0.037*(-1.85)	−0.006 (-0.75)	0.005 (0.56)
CI	−0.165 (-0.89)	−0.244 (-1.26)	−1.086***(-4.87)	−1.040***(-4.77)	−0.230*(-1.83)	0.020 (0.14)
OWN	−0.235***(-3.74)	−0.209***(-3.25)	−0.370***(-5.66)	−0.307***(-4.86)	−0.133***(-3.52)	−0.036 (-0.82)
GDP	0.346***(4.75)	0.294***(4.04)	0.436***(4.28)	0.404***(4.27)	0.998***(18.93)	0.993***(16.84)
Cons	−2.917***(-3.77)	−2.610***(-3.01)	−2.781**(-3.14)	−1.925**(-2.36)	1.593***(3.42)	4.077***(6.85)
α	0.287	0.295	0.315	0.311		
Log pseudo-likelihood	−2469.30	−2474.57	−2800.74	−2798.68		
Wald χ^2	3086.93 [0.00]	2935.77 [0.00]	2517.57 [0.00]	780.00 [0.00]		
R^2					0.860	0.873
F-value					779.75 [0.00]	468.36 [0.00]
Hausman					43.02 [0.00]	39.61 [0.00]
Observations	336	308	336	308	336	308

Note: The t-statistic or z-statistic are in parentheses. P-value is in square brackets. ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively.

respect to invention patents, the input-output cycle is relatively long and its effect is far more lagged.

Models 9 and 10 present the estimated results on the effects of environmental regulation and R&D intensity on value output of the manufacturing industry. The coefficients of ER and ER_{t-1} are not significant, implying that the effect of environmental regulation on value output of the manufacturing industry is not conspicuous. It can be boiled down to two reasons. For one thing, current environmental regulation impairs the outputs of patents and thereby results in the decrease of overall innovation capability of the manufacturing industry. For another, in China's manufacturing industry, the ability to transform technological innovation is inadequate. Technological innovation incurred by environmental regulation has not yet been effectively translated into economic outcomes in the manufacturing industry. The coefficient of R&D is 0.452 ($p < 0.01$), suggesting that R&D intensity significantly raises sales from new products in the manufacturing industry and so does lagged R&D intensity. Likewise, Hashi and Stojčič (2013) also found that R&D intensity can significantly increase sales from new products.

3.4. Productivity

Table 7 shows the estimated results of Eq. (3). To investigate the accumulative effect of the dependent variable, the SYS-GMM method is applied to estimate Eq. (3). Second-order difference residuals of Models 11–18 are irrelevant. The null hypothesis is accepted according to Sargan test, indicating that overidentifying restrictions of instrumental variables do not exist. Therefore, the consistency of SYS-GMM estimator is satisfied.

Models 11 and 12 report the estimated results on the effects of environmental regulation and innovation outputs on labor productivity of the manufacturing industry. The coefficient of DEP_{t-1} is 0.373 ($p < 0.01$), foreshadowing that 1% increase in previous labor productivity will engender 0.373% increase in current labor productivity. The coefficient of ER is 0.003 ($p < 0.01$), meaning that environmental regulation plays a significant role in improving labor productivity. Meanwhile, invention patents, non-invention patents and sales from new products tremendously promote labor productivity, which implies that innovations induced by environmental regulation contribute to the improvement of labor productivity. Similarly, Hamamoto (2006), Yang et al. (2012), Hashi and Stojčič (2013) demonstrated that innovation induced by environmental regulation is an important driving force for manufacturing productivity. On the contrary, the coefficient of ER_{t-1} is −0.003 ($p < 0.01$). It is consistent with Rubashkina et al. (2015). However, the opponents, Berman and Bui (2001), Lanoie et al. (2008), Yang et al. (2012), found that lagged environmental regulation can significantly promote productivity through in-depth case studies of the US, Canada and Taiwan. In the long term, the compliance cost of environmental regulation outstrips the compensation of innovation. Moreover, FDI and ownership type significantly spur labor productivity of the manufacturing industry while capital intensity encumbers it.

Models 13 and 14 display the estimated results on the effects of environmental regulation and innovation outputs on energy efficiency of the manufacturing industry. The coefficient of DEP_{t-1} is 0.888 ($p < 0.01$), suggesting that 1% increase in previous energy

Table 7
Regression results of the productivity equation.

Variable	Labor productivity (LP)		Energy efficiency (ENE)		Environmental efficiency (ENV)		Green total factor productivity (GTFP)	
	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
DEP_{t-1}	0.373***	0.390***	0.888***	0.929***	0.788***	0.778***	0.736***	0.765***
	(19.03)	(15.59)	(14.79)	(16.68)	(27.36)	(18.55)	(25.45)	(19.96)
ER	0.003***		0.020***		0.028**		0.014	
	(3.46)		(5.49)		(2.36)		(0.97)	
ER_{t-1}		−0.003***		0.024***		0.005		0.002
		(-3.34)		(7.98)		(0.47)		(0.17)
PAT	0.018***	0.014***	0.013	0.007	−0.044*	−0.046**	0.033*	0.054**
	(6.43)	(5.22)	(0.82)	(0.40)	(-1.92)	(-2.52)	(1.76)	(2.22)
NPAT	0.023***	0.023***	0.043***	0.038***	0.078***	0.084***	0.009	−0.033
	(10.55)	(8.51)	(3.77)	(2.89)	(2.68)	(3.68)	(0.39)	(-1.57)
NEW	0.020***	0.017***	0.033**	0.035***	−0.033**	−0.027**	0.002	0.018
	(5.45)	(4.00)	(2.48)	(3.11)	(-2.31)	(-1.98)	(0.06)	(0.73)
SUB	0.003	0.005	−0.019	−0.025*	0.054***	0.062***	0.060***	0.068***
	(0.83)	(1.53)	(-1.57)	(-1.82)	(2.70)	(7.01)	(4.16)	(3.36)
FDI	0.017***	0.013***	0.040*	0.036*	−0.001	0.007	0.142*	0.217**
	(3.89)	(2.59)	(1.79)	(1.86)	(-0.01)	(0.27)	(1.94)	(2.47)
MC	−0.0002	−0.0003	0.005**	0.005**	−0.030***	−0.030***	−0.0001	−0.001
	(-0.39)	(-0.47)	(2.24)	(2.08)	(-7.15)	(-6.75)	(-0.01)	(-0.17)
CI	−0.068***	−0.061**	−0.124	−0.142	−0.348***	−0.289***	0.197**	0.180
	(-2.63)	(-2.28)	(-1.40)	(-1.38)	(-3.08)	(-3.07)	(1.97)	(1.62)
OWN	0.030***	0.025***	0.065***	0.039*	−0.166***	−0.127**	−0.143***	−0.086*
	(6.94)	(3.53)	(4.18)	(1.72)	(-2.88)	(-2.32)	(-2.60)	(-1.82)
Cons	0.317***	0.362***	−0.756***	−0.845***	−1.219***	−1.015***	−1.057**	−0.867*
	(7.81)	(6.10)	(-3.38)	(-2.80)	(-3.53)	(-3.78)	(-2.37)	(-1.79)
AR (1)	−3.017	−2.901	−3.250	−3.130	−2.128	−2.140	−2.125	−2.112
	[0.00]	[0.00]	[0.00]	[0.00]	[0.03]	[0.03]	[0.03]	[0.03]
AR (2)	0.556	0.103	−1.287	−0.820	−0.035	−0.010	−0.035	−0.033
	[0.58]	[0.92]	[0.20]	[0.41]	[0.97]	[0.99]	[0.97]	[0.97]
Sargan χ^2	24.690	25.819	24.493	24.419	20.793	21.293	17.320	20.41
	[1.00]	[0.99]	[1.00]	[1.00]	[0.98]	[0.98]	[1.00]	[0.98]
Wald χ^2	28,829.61	21,917.36	6668.50	12,813.60	28,364.34	25,391.80	6932.12	4403.61
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	280	280	280	280	308	308	308	308

Note: The z-statistics are in parentheses. P-value is in square brackets. ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively.

efficiency will generate 0.888% increase in current energy efficiency. The coefficients of ER and ER_{t-1} are 0.02 ($p < 0.01$) and 0.024 ($p < 0.01$), respectively, indicating that environmental regulation can significantly propel energy efficiency but its efficacy is lagged. Keeping with the above results, Zhou and Feng (2017) found that environmental regulation contributes to reducing energy consumption and improving energy efficiency through technological progress. Drawing on the experience of German manufacturing companies, Schulze and Heidenreich (2017) also contended that official management and control measures can improve energy efficiency. The increased effect of invention patents on energy efficiency is not apparent. The reason lies in that in China's manufacturing industry, invention patents for energy conservation are less than that for improving labor productivity. Non-invention patents and sales from new products significantly facilitate energy efficiency because technological transformation of China's manufacturing industry necessitates non-invention patents. More precisely, the amelioration of technological process and product appearance tends to efficiently drive down energy consumption (Zhou and Feng, 2017). Additionally, the translation of non-invention patents into value output is conducive to a win-win for industrial economic development and energy conservation.

Models 15 and 16 present the estimated results about the effects of environmental regulation and innovation outputs on environmental efficiency of the manufacturing industry. The coefficient of DEP_{t-1} is 0.788 ($p < 0.01$), indicating that 1% increase in previous environmental efficiency results in 0.788% increase in current environmental efficiency. The coefficient of ER is 0.028 ($p < 0.05$) and it implies that environmental regulation has a significantly positive effect on environmental efficiency. This result is consistent with the conclusions of Wang and Shen (2016), Ramanathan et al. (2017), Graafland and Smid (2017), Prasad and Mishra (2017), who also stressed that environmental regulation can improve environmental performance in the industry or enterprise. Conversely, the galvanizing effect of lagged environmental regulation on environmental efficiency is not prominent in that enforcement is selectively exercised in the process of implementing environmental policies in China's manufacturing industry (Cory and Rahman, 2009); that is, enforcement is exercised in ways that vary dramatically from the conventional prescriptions of economic deterrence theory. Violators are frequently not pursued at all or pursued with expected penalties that are inconsequential. With the continued enforcement of environmental policies, selective implementation becomes increasingly severe. Invention patents significantly obstruct environmental efficiency, which suggests that at present, invention patents in China's manufacturing industry mainly aim to boost economic performance regardless of environmental consequences. Sun et al. (2008) has pointed out that the ability of China's environmental technology innovation was still weak, because it was estimated that environmental patents accounted for a relatively small percentage in total patents. Whereas the role of non-invention patents in promoting environmental efficiency is significant, indicating that the manufacturing industry conforms to environmental regulation through innovation on non-invention patents that highlight process innovation. This innovation is characterized by low cost and fast effect and accords with the double needs of economic development and environmental protection. The scholars in this arena like Carrión-Flores and Innes (2010), Gilli et al. (2014), Costantini et al. (2017) also asserted that eco-innovation can help to realize the improvement of industrial environmental efficiency. In contrast, sales from new products significantly inhibits the growth of environmental efficiency, which is ascribed to current limited environmental regulation intensity. Under this circumstance, for the manufacturing enterprises, the internalized degree of negative externalities is relatively low, thus leading to the waning of devotion to environmental protection in the development of enterprises.

Models 17 and 18 report the estimated results on the effects of environmental regulation and innovation outputs on GTFP of the manufacturing industry. The coefficient of DEP_{t-1} is 0.736 ($p < 0.01$), meaning that 1% increase in previous GTFP will result in 0.736% increase in current GTFP. Neither current nor lagged environmental regulation has a significantly stimulating effect on GTFP. The result is basically consistent with the conclusion of Yuan et al. (2017). They argued that current environmental regulation is incapable of improving eco-efficiency of the manufacturing industry. Conversely, Li and Wu (2017) studied 273 cities in China and found that local environmental regulation can significantly promote GTFP. Based on the sample of China's provinces, Xie et al. (2017) concluded that command-and-control and market-based environmental regulations have significantly non-linear and positive effects on green productivity. Notwithstanding the improvements in energy efficiency and environmental efficiency of the manufacturing industry enticed by environmental regulation, the emergence of rebound effect leads to increased energy consumption and aggravated environmental damage and thus GTFP is not significantly improved. Furthermore, current environmental policies in China are not systematic and comprehensive so that they can not work together to energize green development of the manufacturing industry. Specifically, the fragmentization of policies makes the firms' emphasis placed on environmental protection vacillate between energy consumption and emission reduction. As a result, the coordinated development of economy, energy and environment in the manufacturing industry is difficult to be achieved. The coefficient of PAT is 0.033 ($p < 0.1$), indicating that invention patents significantly promote the improvement of GTFP. Our rationale is that invention patents accelerate economic expansion of the manufacturing industry, substantially increase desirable outputs of GTFP and bring down redundancy rate of energy and environmental investments. Tian and Lin (2017) and Li et al. (2018) support the result and they claimed that technological innovation is essential to drive the growth of China's industrial green productivity. As opposed to invention patents, non-invention patents are not significantly advantageous to GTFP of the manufacturing industry on account that they are regarded as a strategic measure to implement environmental regulation considering that firms are only concerned about the unidimensional attribute of them, i.e. energy conservation or environmental protection and forsake the fulfillment of the coordinated development of environment and economy. Economic development of China's manufacturing industry is not totally decoupled from environmental damage (Ren and Hu, 2012). Economic boom may be accompanied by severer environmental damage. For this reason, sales from new products do not significantly promote GTFP.

3.5. Robustness tests

In this paper, we conduct robustness tests in following two ways. First, to rule out the potential impact of industry size, environmental regulation intensity (operating cost of pollution treatment facilities/total output value of the industry) is adopted as an indicator for environmental regulation (Levinson and Taylor, 2008). In Eq. (2), we use the number of invention patents in force as a proxy for invention patents and the number of non-invention patents in force for non-invention patents. The regression results are shown in Models 19–26 of Table 8. Second, SO_2 emission intensity is employed to measure the level of environmental regulation (Domazlicky and Weber, 2004) for the purpose of examining the impacts of different measures for environmental regulation and their errors. See the regression results in Models 27–34 of Table 8.

Table 8
Robustness tests.

	Model 19 (R&D)	Model 20 (PAT)	Model 21 (NPAT)	Model 22 (NEW)	Model 23 (LP)	Model 24 (ENE)	Model 25 (ENV)	Model 26 (GTFP)	Model 27 (R&D)	Model28 (PAT)	Model 29 (NPAT)	Model 30 (NEW)	Model 31 (LP)	Model 32 (ENE)	Model 33 (ENV)	Model 34 (GTFP)
DEP_{t-1}	0.502***				0.364***	0.923***	0.778***	0.743***	0.498***				0.357***	0.907***	0.419***	0.705***
	(17.24)				(19.18)	(15.75)	(26.32)	(26.02)	(20.02)				(17.06)	(15.28)	(11.71)	(16.38)
R&D		0.197***	0.233***	0.452***						0.159***	0.189***	0.453***				
		(3.72)	(4.30)	(10.51)						(3.41)	(3.91)	(10.57)				
ER	−0.026	−0.148***	−0.163***	0.011	0.003***	0.011**	0.024*	0.011	−0.011	−0.208***	−0.208***	0.038	0.011***	0.054***	0.394***	0.168
	(-1.55)	(-4.60)	(-6.07)	(0.64)	(2.72)	(2.13)	(1.69)	(0.82)	(-0.28)	(-10.14)	(-9.90)	(1.54)	(4.25)	(3.68)	(12.85)	(1.24)
PAT					0.016***	0.013	−0.033*	0.041*					0.017***	0.009	−0.010**	0.041**
					(5.43)	(0.82)	(-1.67)	(1.94)					(5.84)	(0.52)	(-1.69)	(2.04)
NPAT					0.025***	0.042***	0.052**	0.003					0.026***	0.046***	0.0005**	0.070
					(10.18)	(3.37)	(1.98)	(0.16)					(10.12)	(4.60)	(2.02)	(0.97)
NEW					0.025***	0.038***	−0.007**	0.016					0.029***	0.054***	−0.056***	0.039
					(6.36)	(2.96)	(-2.25)	(0.47)					(7.31)	(4.02)	(-3.70)	(1.21)
LAB		0.388***	0.413***	−0.011						0.323***	0.352***	−0.007				
		(6.51)	(6.64)	(-0.38)						(5.84)	(5.98)	(-0.23)				
TI		0.466***	0.485***	0.004						0.527***	0.553***	−0.002				
		(6.81)	(6.52)	(0.12)						(9.04)	(8.46)	(-0.05)				
SUB	0.004	0.130***	0.180***	0.008	−0.0001	−0.018**	0.064***	0.064***	0.028	0.116***	0.164***	0.008	−0.001	−0.022**	0.057***	0.068***
	(0.17)	(2.93)	(3.95)	(0.30)	(-0.03)	(-1.68)	(4.72)	(4.05)	(1.14)	(2.95)	(3.95)	(0.31)	(-0.26)	(-2.02)	(3.38)	(5.12)
FDI	−0.471***	0.050	0.011	−0.215***	0.003*	0.048**	0.012	0.182**	−0.466***	−0.062	−0.098**	−0.215***	0.004*	0.024	−0.228**	−0.018
	(-5.60)	(1.02)	(0.21)	(-4.66)	(1.69)	(1.99)	(0.48)	(2.00)	(-4.59)	(-1.34)	(-2.03)	(-4.68)	(1.85)	(1.26)	(-2.14)	(-0.15)
MC	0.113***	0.002	0.005	−0.006	−0.0005	0.004**	−0.027***	0.002	0.114***	0.032**	0.032**	−0.007	−0.0005	0.001	−0.013***	−0.001
	(18.88)	(0.14)	(0.28)	(-0.75)	(-0.75)	(2.58)	(-4.45)	(0.39)	(19.66)	(2.07)	(2.01)	(-0.88)	(-1.39)	(0.44)	(-3.25)	(-0.24)
CI	−0.712***	−0.303*	−0.276*	−0.230*	−0.082***	−0.074	−0.344***	0.186*	−0.597***	0.292*	0.273	−0.232**	−0.115***	−0.110*	0.057	0.496***
	(-3.40)	(-1.91)	(-1.73)	(-1.83)	(-3.17)	(-1.20)	(-3.00)	(1.85)	(-3.52)	(1.71)	(1.56)	(-1.89)	(-5.36)	(-1.72)	(0.35)	(3.55)
OWN	0.216***	−0.074	−0.117**	−0.133***	0.025***	0.056***	−0.171***	−0.123**	0.207***	−0.022	−0.062	−0.145	0.017***	0.026	−0.147***	−0.083
	(7.50)	(-1.39)	(-2.09)	(-3.52)	(4.83)	(2.95)	(-0.84)	(-2.13)	(4.40)	(-0.46)	(-1.24)	(-3.82)***	(3.31)	(0.95)	(-2.84)	(-1.39)
GDP	0.131***	0.157***	0.165***	0.998***					0.144**	0.075	0.081	1.038***				
	(3.26)	(2.77)	(2.91)	(18.93)					(2.44)	(1.44)	(1.52)	(19.70)				
Cons	1.868***	−0.430	−1.830**	1.593***	0.303***	−0.490**	−1.449***	−0.969*	1.893***	−0.138	−1.384**	1.650***	0.275***	−0.472**	−4.550***	−1.432***
	(4.50)	(-0.58)	(-2.37)	(3.42)	(6.81)	(-2.15)	(-2.61)	(-1.75)	(6.48)	(-0.22)	(-2.05)	(3.63)	(6.11)	(-2.56)	(-9.91)	(-2.67)
AR (1)	−3.53				−2.91	−3.30	−2.12	−2.15	−3.37				−2.64	−3.24	−2.08	−2.00
	[0.00]				[0.00]	[0.00]	[0.03]	[0.03]	[0.00]				[0.01]	[0.00]	[0.04]	[0.05]
AR (2)	0.097				0.45	−1.19	−0.02	−0.03	0.192				0.04	−1.64	−0.22	−0.279
	[0.92]				[0.65]	[0.23]	[0.99]	[0.97]	[0.85]				[0.97]	[0.11]	[0.82]	[0.78]
Sarganχ^2	24.22				24.60	23.59	21.12	17.36	25.64				25.42	24.50	22.71	17.51
	[0.99]				[0.88]	[1.00]	[0.98]	[1.00]	[0.98]				[0.86]	[0.88]	[0.96]	[1.00]
α		0.219	0.228							0.181	0.195					
Log pseudo-likelihood		−2590.62	−2535.27							−2556.48	−2507.05					
R^2				0.860								0.846				
F-value				779.76 [0.00]								785.07 [0.00]				
Wald χ^2	1904.53	1859.87	2412.90		20,311.49	16,774.97	33,605.69	10,267.50	3725.64	2621.41	3056.30		20,909.16	37,209.15	5826.85	13,317.41
	[0.00]	[0.00]	[0.00]		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]		[0.00]	[0.00]	[0.00]	[0.00]
Observations	252	336	336	336	280	280	308	308	252	336	336	336	280	280	308	308

Note: The *t*-statistic or *z*-statistic are in parentheses. *P*-value is in square brackets. ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively.

In Table 8, environmental regulation has an insignificantly negative effect on R&D intensity of the manufacturing industry compared with Table 5. The effects of environmental regulation and R&D intensity on invention patents, non-invention patents and sales from new products are consistent with Table 6 while the coefficients and significance are slightly different. Besides, the effects of environmental regulation and innovation outputs on labor productivity, energy efficiency, environmental efficiency and GTFP are in keeping with Table 7 and only their coefficients and significance are not identical. Therefore, the empirical results of this paper are robust and reliable. For the sake of limited space, Table 8 merely reports estimation coefficients and test results of key independent variables and leaves out the estimation results of lagged environmental regulation.

4. Conclusions

This paper draws the conclusions below. First, in the short term, the effect of environmental regulation on R&D investment of the manufacturing industry is not evident. But in the long term, environmental regulation has a crowding out effect on R&D investment, indicating that innovation initiatives in the manufacturing industry are typically deterred by the compliance cost of environmental regulation, that is, enterprises must curtail R&D expenditures to deal with the continuously enhanced environmental regulation when facing multiple constraints of economic growth, energy sources and ecological environment. The conclusions are in line with Kneller and Manderson (2012) and Rubashkina et al. (2015). Arguably, they also find that environmental regulation does not have a significantly positive impact on R&D investment of the manufacturing industry. However, the views of this paper do not coincide with Zhao and Sun (2016), the findings of which suggest that environmental regulation plays a weak role in boosting R&D investment because financial subsidy and tax preference from the government obtained by pollution-intensive enterprises overcompensate the compliance cost. Unlike that, the focal point of this paper is the effect of environmental regulation on overall innovation input of the manufacturing industry. This paper suggests that policymakers should be vigilant about the impairing effect of environmental regulation on R&D investment of the manufacturing industry.

Second, environmental regulation has significantly inhibited the outputs of non- and invention patents in the manufacturing industry and the inhibitory effect on invention patents is stronger than that on non-invention patents. It manifests that in the first phase of innovation, R&D investment of the manufacturing industry constantly dwindles owing to the crowding out effect of environmental regulation, thus seriously constraining the outputs of patents in the second phase, which is in keeping with the conclusions of Blind (2012). The stimulating effect of environmental regulation on sales from new products of the manufacturing industry is not significant since value output in the stage of innovation transformation is negatively influenced by the decrease of patents, thus providing no support for “weak” Porter hypothesis. Innovation input is inclined to significantly foster non- and invention patents as well as sales from new products in the manufacturing industry, which is parallel with the opinions of Acosta et al. (2015), demonstrating that to enhance investments in innovation is an important avenue towards increased innovation outputs.

Third, in the short term, environmental regulation can promote the improvements of labor productivity, energy efficiency and environmental efficiency of the manufacturing industry but not for GTFP. The “strong” Porter hypothesis is thus not underpinned. For the policymakers, more attention should be paid to the concerted effect of environmental and innovation policies so as to be insured against the deviation of the policy intervention endeavor from the coordinated development of economy, energy and environment of the manufacturing industry. In the long term, environmental regulation solely exerts a positive effect on energy efficiency of the manufacturing industry whilst it has a significantly inhibitory effect on labor productivity and an insignificant effect on environmental efficiency and GTFP, which bespeaks that economic development of the manufacturing industry is stagnant as a result of the crowding out effect on R&D investment caused by environmental regulation being transferred to the industrial production process; moreover, Chinese environmental policies with short-term objectives have been enforced intensely and temporarily for a long time so that the stable improvements of environmental efficiency and GTFP are fraught with difficulties to be achieved.

Fourth, the galvanizing effect of invention patents is significant on labor productivity and GTFP of the manufacturing industry and insignificant on energy efficiency. Additionally, the improvement of environmental efficiency is held back. It is inconsistent with Marin (2014) who posits that technological progress can reduce pollutant discharge intensity by enhancing resource utilization efficiency in production activities, thereby increasing environmental efficiency. The reason accounting for the different findings above lies in that invention patents aggravate the tension between labor productivity and environmental protection in the manufacturing industry-that is, economic expansion caused by this innovation leads to the rebound effect of reduced energy use and environmental damage. Non-invention patents play a significantly positive role in promoting labor productivity, energy efficiency and environmental efficiency but an inconsequential role in the improvement of GTFP, which implies that the manufacturing industry prefers strategic innovation outputs to respond to environmental regulation, irrespective of the unproductive integrated effect of economy, energy and environment. Sales from new products can significantly promote labor productivity and energy efficiency of the manufacturing industry but repress the improvement of environmental efficiency, indicating that value output is able to strengthen economic performance of the enterprises, whereas it is realized at the expense of natural environment and thus, the improvement of GTFP is hampered.

Our findings make several contributions to policy implications. First, the government may as well reduce the compliance cost for the industries when formulating environmental regulations. On the one hand, the goal of environmental policy should keep pace with the practices of the manufacturing industry by improving the systems concerning environmental information disclosure and environmental supervision. On the other hand, to further reduce the compliance cost and increase the efficiency of environmental regulation, the government is suggested to set up effective market mechanisms of energy and environmental protection, for example, promoting the widespread application of market-based tools such as emissions trading, resource tax, environmental tax, etc.

Second, as invention patents can promote economic development of the manufacturing industry but significantly inhibit the improvement of environmental efficiency, the technological structure of China's manufacturing industry needs to be adjusted. In doing so, the government should encourage the manufacturing industry to launch innovation initiatives on low carbon and energy conservation through financial subsidy, tax preference, etc. Non-invention patents are able to impel the coordinated development of economy, energy and environment in the manufacturing industry and thus, the government should give impetus to the manufacturing industry to introduce facilities for energy conservation and emission reduction as well as intensify innovation investment in green technologies so as to quicken the renovation of green processes of the manufacturing industry.

Third, the commercialization of green innovation in the manufacturing industry should be enhanced. To attain this target, a favorable environment should be established by reinforcing the synergy of fiscal, tax, industrial, financial and government procurement policies and optimizing public services. According to the statistics of Ministry of Industry and Information Technology, current transformation rate of S&T (scientific and technological) achievements was less than 10% while that of developed countries reached up to 40%–50%.[1] Consequently, the industrialization of green S&T outcomes should be accelerated and then turned into powerful green productivity to promote green development of the manufacturing industry.

Fourth, our results show that environment regulation has not improved GTFP of the manufacturing industry. Therefore, the government should focus on the overall goal of green development in the manufacturing industry and formulate systematic policies for the coordinated development of economy, energy and environment. Allowing for the combined effect of environmental regulation and innovation on economy, energy and environment, corresponding policy portfolios are indispensable to green development of the manufacturing industry. Whereupon, the government should not treat only the head when the head aches, and the foot when the foot hurts and should abandon these traditional fragmented industrial policies. Instead, the continuity, consistency and steadiness of environmental policies implemented are supposed to be guaranteed.

Our results point in several potentially fruitful directions for future research. First, considering the availability of industrial data, a single indicator–"operating cost of pollution treatment facilities" is used as a measure for environmental regulation. We do not further compartmentalize environmental regulation on the basis of mandatory degree. Subsequent studies can explore the effect of a certain type of environmental regulation or an energy and environmental policy on industrial innovation and green development. Second, we merely include overall innovation outputs of the manufacturing industry and has not yet considered patent's attributes for energy conservation and emission reduction. Future research can center on green patents by grouping them into resource-saving, energy-conservation and environment-friendly patents and analyzing the impacts of different types of green patents on green development of the manufacturing industry.

Acknowledgements

This research work is supported by the National Natural Science Foundation of China (71703171), by Social Science Achievement Evaluation Committee of Hunan Province (XSP17YBZZ144), and by the Colleges and Universities Innovation Platform Open Foundation of Hunan Province (16K106). The authors also would like to thank the anonymous reviewers for their insightful comments.

Appendix

The super efficiency DEA model (SE-DEA) to evaluate energy efficiency, environmental efficiency and GTFP of China's manufacturing industry is displayed as Eq. (A.1).

$$\min \rho_{SE} = \frac{1+\frac{1}{m}\sum_{i=1}^{m} s_i^- \Big/ x_{ik}}{1-\frac{1}{q}\sum_{r=1}^{q} s_r^+ \Big/ y_{rk}} s.t. \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik} \sum_{j=1, j\neq k}^{n} y_{rj}\lambda_j + s_r^+ \geq y_{rk}\lambda, s^-, s^+ \geq 0 \;\; i=1,2,\ldots,m; r = 1,2,\ldots,q; j=1,2,\ldots,n (j\neq k) \tag{A.1}$$

where m and q represent the input and the output of each DMU respectively. n denotes the number of DMU and $\rho$is the efficiency value. x_{ij} is the i input of the j DMU. $y_{rj}$is the r output of the j DMU. $s^-$and $s^+$are the slack variables of inputs, outputs respectively. See the results in Figs. A.1-A.3.

Table A.1
Industry code and name

Code	Sector	Code	Sector
M1	Processing of Food from Agricultural Products	M15	Manufacture of Medicines
M2	Manufacture of Foods	M16	Manufacture of Chemical Fibers
M3	Manufacture of Beverages	M17	Manufacture of Rubber and Plastics
M4	Manufacture of Tobacco	M18	Manufacture of Non-metallic Mineral Products
M5	Manufacture of Textile	M19	Smelting and Pressing of Ferrous Metals
M6	Manufacture of Textile Wearing Apparel, Footware and Caps	M20	Smelting and Pressing of Non-ferrous Metals
M7	Manufacture of Leather, Fur, Feather and Related Products	M21	Manufacture of Metal Products
M8	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products	M22	Manufacture of General Purpose Machinery
M9	Manufacture of Furniture	M23	Manufacture of Special Purpose Machinery
M10	Manufacture of Paper and Paper Products	M24	Manufacture of Transport Equipment
M11	Printing, Reproduction of Recording Media	M25	Manufacture of Electrical Machinery and Equipment
M12	Manufacture of Articles for Culture, Education and Sport Activity	M26	Manufacture of Communication Equipment, Computers and Other Electronic Equipment
M13	Processing of Petroleum, Coking, Processing of Nuclear Fuel	M27	Manufacture of Measuring Instruments and Machinery for Cultural Activity and Office Work
M14	Manufacture of Raw Chemical Materials and Chemical Products	M28	Manufacture of Artwork and Other Manufacturing

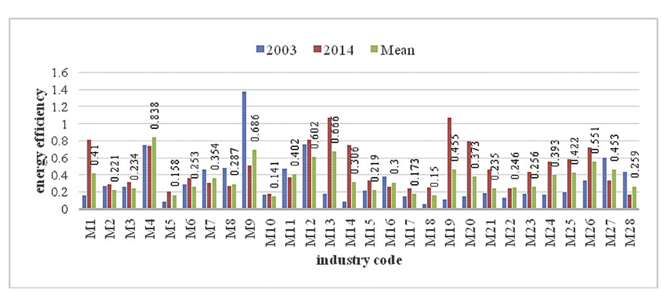

Fig. A.1. The energy efficiency of every industry in China's manufacturing sector.

[1] http://www.miit.gov.cn/n1146285/n1146352/n3054355/n3057497/n3057504/c3609139/content.html.

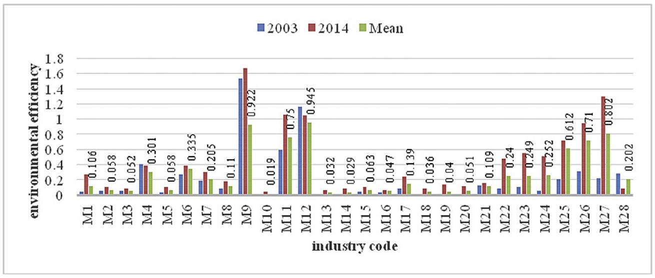

Fig. A.2. The environmental efficiency of every industry in China's manufacturing sector.

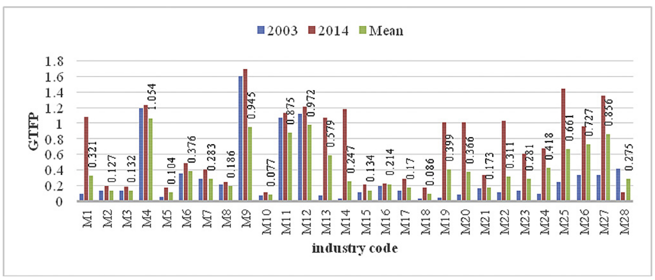

Fig. A.3. The GTFP of every industry in China's manufacturing sector.

References

Hashi, I., Stojčič, N., 2013. The impact of innovation activities on firm performance using a multi-stage model: evidence from the Community Innovation Survey 4. Res. Policy 42, 353–366.

Acosta, M., Coronado, D., Romero, C., 2015. Linking public support, R&D, innovation and productivity: new evidence from the Spanish food industry. Food Policy 57, 50–61.

Albrizio, S., Kozluk, T., Zipperer, V., 2017. Environmental policies and productivity growth: evidence across industries and firms. J. Environ. Econ. Manag. 81, 209–226.

Amores-Salvadó, J., Castro, G.M., Navas-López, J.E., 2014. Green corporate image: moderating the connection between environmental product innovation and firm performance. J. Clean. Prod. 83, 356–365.

Amores-Salvadó, J., Castro, G.M., Navas-López, J.E., 2015. The importance of the complementarity between environmental management systems and environmental innovation capabilities: a firm level approach to environmental and business performance benefits. Technol. Forecast. Soc. Change 96, 288–297.

Baumann, J., Kritikos, A.S., 2016. The link between R&D, innovation and productivity: are micro firms different? Res. Policy 45, 1263–1274.

Benavente, J.M., 2002. The role of research and innovation in promoting productivity in Chile. Econ. Innovat. New Technol. 15 (15), 301–315, 2002.

Berman, E., Bui, L.T.M., 2001. Environmental regulation and productivity: evidence from oil refineries. Rev. Econ. Statistics 83, 498–510.

Blind, K., 2012. The influence of regulations on innovation: a quantitative assessment for OECD countries. Res. Policy 41, 391–400.

Bond, S., 2002. Dynamic panel data models: a guide to micro data methods and practice. Portuguese Econ. J. 1 (2), 141–162.

Brunneimer, S., Cohen, M., 2003. Determinants of environmental innovation in US manufacturing industries. J. Environ. Econ. Manag. 45, 278–293.

Carrión-Flores, C.E., Innes, R., 2010. Environmental innovation and environmental performance. J. Environ. Econ. Manag. 59, 27–42.

Chakraborty, P., Chatterjee, C., 2017. Does environmental regulation indirectly induce upstream innovation? New evidence from India. Res. Policy 46, 939–955.

Chang, S.J., Chung, J., Moon, J.J., 2013. When do wholly owned subsidiaries perform better than joint ventures? Strategic Manag. J. 34, 317–337.

Chen, S.Y., Golley, J., 2014. 'Green' productivity growth in China's industrial economy. Energy Econ. 44, 89–98.

Chudnovsky, D., López, A., Pupato, G., 2006. Innovation and productivity in developing countries: a study of Argentine manufacturing firms' behavior (1992–2001). Res. Policy 35, 266–288.

Cory, D.C., Rahman, T., 2009. Environmental justice and enforcement of the safe drinking water act: the Arizona arsenic experience. Ecol. Econ. 68, 1825–1837.

Costa-Campi, M.T., Duch-Brown, N., García-Quevedo, J., 2014. R&D drivers and obstacles to innovation in the energy industry. Energy Econ. 46, 20–30.

Costa-Campi, M.T., García-Quevedo, J., Martínez-Ros, E., 2017. What are the determinants of investment in environmental R&D? Energy Policy 104, 455–465.

Costantini, V., Crespi, F., Marin, G., Paglialunga, E., 2017. Eco-innovation, sustainable supply chains and environmental performance in European industries. J. Clean. Prod. 155, 141–154.

Crépon, B., Duguet, E., Mairesse, J., 1998. Research, innovation and productivity: an econometric analysis at the firm level. Econ. Innovat. New Technol. 7 (2), 115–158.

Domazlicky, B.R., Weber, W.L., 2004. Does environmental protection lead to slower productivity growth in the chemical industry? Environ. Resour. Econ. 28, 301–324.

Dosi, G., Marengo, L., Pasquali, C., 2006. How much should society fuel the greed of innovators? On the relations between appropriability, opportunities and rates of innovation. Res. Policy 35, 1110–1121.

Frank, A.G., Cortimiglia, M.N., Ribeiro, J.L.D., Oliveira, L.S., 2016. The effect of innovation activities on innovation outputs in the Brazilian industry: market-orientation vs. technology-acquisition strategies. Res. Policy 45, 577–592.

Ghisetti, C., Pontoni, F., 2015. Investigating policy and R&D effects on environmental innovation: a meta-analysis. Ecol. Econ. 118, 57–66.

Ghisetti, C., Rennings, K., 2014. Environmental innovations and profitability: how does it pay to be green? An empirical analysis on the German innovation survey. J. Clean. Prod. 75, 106–117.

Gilli, M., Mancinelli, S., Mazzanti, M., 2014. Innovation complementarity and environmental productivity effects: reality or delusion? Evidence from the EU. Ecol. Econ. 103, 56–67.

Graafland, J., Smid, H., 2017. Reconsidering the relevance of social license pressure and government regulation for environmental performance of European SMEs. J. Clean. Prod. 141, 967–977.

Gray, W.B., Shadbegian, R.J., 2003. Plant vintage, technology, and environmental regulation. J. Environ. Econ. Manag. 46 (3), 384–402.

Guo, P.B., Wang, T., Li, D., Zhou, X.J., 2016. How energy technology innovation affects transition of coal resource-based economy in China. Energy Policy 92, 1–6.

Hall, B.H., Harhoff, D., 2012. Recent research on the economics of patents. Annu. Rev. Econ. 4, 541–565.

Hall, B.H., Griliches, Z., Hausman, J.A., 1986. Patents and R&D: is there a lag? Int. Econ. Rev. 27, 265–284.

Hamamoto, M., 2006. Environmental regulation and the productivity of Japanese manufacturing industries. Resour. Energy Econ. 28, 299–312.

Horbach, J., 2008. Determinants of environmental innovation-new evidence from German panel data sources. Res. Policy 37, 163–173.

Horbach, J., Rammer, C., Rennings, K., 2012. Determinants of eco-innovations by type of environmental impact-The role of regulatory push/pull, technology push and market pull. Ecol. Econ. 78, 112–122.

Jaffe, A., Palmer, K., 1997. Environmental regulation and innovation: a panel study. Rev. Econ. Statistics 79, 610–619.

Kao, C., 1999. Spurious regression and residual-based tests for cointegration in panel data. J. Econ. 90 (1), 1–44.

Kesidou, E., Demirel, P., 2012. On the drivers of eco-innovations: empirical evidence from the UK. Res. Policy 41, 862–870.

Kim, B., Kim, E., Miller, D.J., Mahoney, J.T., 2016. The impact of the timing of patents on innovation performance. Res. Policy 45, 914–928.

Kneller, R., Manderson, E., 2012. Environmental regulations and innovation activity in UK manufacturing industries. Resour. Energy Econ. 34, 211–235.

Lanoie, P., Patry, M., Lajeunesse, R., 2008. Environmental regulation and productivity: testing the porter hypothesis. J. Prod. Anal. 30 (2), 121–128.

Lee, K.H., Min, B., 2015. Green R&D for eco-innovation and its impact on carbon emissions and firm performance. J. Clean. Prod. 108, 534–542.

Levinson, A., Taylor, M.S., 2008. Unmasking the pollution haven effect. Int. Econ. Rev. 49 (1), 223–254.

Li, K., Lin, B.Q., 2016. Impact of energy conservation policies on the green productivity in China's manufacturing sector: evidence from a three-stage DEA model. Appl. Energy 168, 351–363.

Li, K., Lin, B.Q., 2017. Economic growth model, structural transformation, and green productivity in China. Appl. Energy 187, 489–500.

Li, B., Wu, S.S., 2017. Effects of local and civil environmental regulation on green total factor productivity in China: a spatial Durbin econometric analysis. J. Clean. Prod. 153, 342–353.

Li, W.J., Zheng, M.N., 2016. Is it substantive innovation or strategic innovation? Impact of macroeconomic policies on micro-enterprises' innovation. Econ. Res. J. 4, 60–73 (Chinese periodicals).

Li, W.W., Wang, W.P., Wang, Y., Ali, M., 2018. Historical growth in total factor carbon productivity of the Chinese industry - a comprehensive analysis. J. Clean. Prod. 170, 471–485.

Lin, B.Q., Zhao, H.L., 2016. Technology gap and regional energy efficiency in China's textile industry: a non-parametric meta-frontier approach. J. Clean. Prod. 137, 21–28.

Lin, B.Q., Zheng, Q.Y., 2017. Energy efficiency evolution of China's paper industry. J. Clean. Prod. 140, 1105–1117.

Mairesse, J., Mohnen, P., Kremp, E., 2005. The importance of R&D and innovation for productivity: a reexamination in light of the French innovation survey. Ann. Econ. Statistics 79/80, 487–527.

Marchi, V.D., 2012. Environmental innovation and R&D cooperation: empirical evidence from Spanish manufacturing firms. Res. Policy 41, 614–623.

Marin, G., 2014. Do eco-innovations harm productivity growth through crowding out? Results of an extended CDM model for Italy. Res. Policy 43, 301–317.

Meng, F.Y., Su, B., Thomson, E., Zhou, D.Q., Zhou, P., 2016. Measuring China's regional energy and carbon emission efficiency with DEA models: a survey. Appl. Energy 183, 1–21.
Porter, M.E., van der Linde, C., 1995. Toward a new conception of the environment-competitiveness relationship. J. Econ. Perspective 9, 97–118.
Prasad, M., Mishra, T., 2017. Low-carbon growth for Indian iron and steel sector: exploring the role of voluntary environmental compliance. Energy Policy 100, 41–50.
Przychodzen, J., Przychodzen, W., 2015. Relationships between eco-innovation and financial performance - evidence from publicly traded companies in Poland and Hungary. J. Clean. Prod. 90, 253–263.
Ramanathan, R., He, Q.L., Black, A., Ghobadian, A., Gallear, D., 2017. Environmental regulations, innovation and firm performance: a revisit of the Porter hypothesis. J. Clean. Prod. 155, 79–92.
Raymond, W., Mairesse, J., Mohnen, P., Palm, F., 2015. Dynamic models of R&D, innovation and productivity: panel data evidence for Dutch and French manufacturing. Eur. Econ. Rev. 78, 285–306.
Ren, S.G., Hu, Z., 2012. Effects of decoupling of carbon dioxide emission by Chinese nonferrous metals industry. Energy Policy 43, 407–414.
Ren, S.G., Yuan, B.L., Ma, X., Chen, X.H., 2014. The impact of international trade on China's industrial carbon emissions since its entry into WTO. Energy Policy 69, 624–634.
Ren, S.G., Li, X.L., Yuan, B.L., Li, D.Y., Chen, X.H., 2016. The effects of three types of environmental regulation on eco-efficiency: a cross-region analysis in China. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2016.08.113 (in press).
Rubashkina, Y., Galeotti, M., Verdolini, E., 2015. Environmental regulation and competitiveness: empirical evidence on the Porter Hypothesis from European manufacturing sectors. Energy Policy 83, 288–300.
Schulze, M., Heidenreich, S., 2017. Linking energy-related strategic flexibility and energy efficiency- the mediating role of management control systems choice. J. Clean. Prod. 140, 1504–1513.
Song, C., Oh, W., 2015. Determinants of innovation in energy intensive industry and implications for energy policy. Energy Policy 81, 122–130.
Sun, Y.M., Lu, Y.L., Wang, T.Y., Ma, H., He, G.Z., 2008. Pattern of patent-based environmental technology innovation in China. Technol. Forecast. Soc. Change 75, 1032–1042.
Tian, P., Lin, B.Q., 2017. Promoting green productivity growth for China's industrial exports: evidence from a hybrid input-output model. Energy Policy 111, 394–402.
Wang, Z.H., Feng, C., 2015. A performance evaluation of the energy, environmental, and economic efficiency and productivity in China: an application of global data envelopment analysis. Appl. Energy 147, 617–626.
Wang, Y., Shen, N., 2016. Environmental regulation and environmental productivity: the case of China. Renew. Sustain. Energy Rev. 62, 758–766.
Xie, R.H., Yuan, Y.J., Huang, J.J., 2017. Different types of environmental regulations and heterogeneous influence on “green” productivity: evidence from China. Ecol. Econ. 132, 104–112.
Yan, X., Fang, Y.P., 2015. CO_2 emissions and mitigation potential of the Chinese manufacturing industry. J. Clean. Prod. 103, 759–773.
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, 514–532.
Yuan, B.L., Ren, S.G., Chen, X.H., 2017. Can environmental regulation promote the coordinated development of economy and environment in China's manufacturing industry?—A panel data analysis of 28 sub-sectors. J. Clean. Prod. 149, 11–24.
Zhang, C.H., Liu, H.Y., 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, 2369–2379.
Zhang, Z.L., Xue, B., Chen, X.P., Li, Y.J., 2015. Convergence in spatial difference of industrial environmental efficiency in China. China Population. Resour. Environ. 25 (2), 30–38 (Chinese periodicals).
Zhao, X., Sun, B.W., 2016. The influence of Chinese environmental regulation on corporation innovation and competitiveness. J. Clean. Prod. 112, 1528–1536.
Zhao, C.F., Chen, B., Hayat, T., Alsaedi, A., Ahmad, B., 2014. Driving force analysis of water footprint change based on extended STIRPAT model: evidence from the Chinese agricultural sector. Ecol. Indic. 47, 43–49.
Zhou, X.X., Feng, C., 2017. The impact of environmental regulation on fossil energy consumption in China: direct and indirect effects. J. Clean. Prod. 142, 3174–3183.