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Investigating the role of emissions trading policy to reduce emissions and improve the efficiency of industrial green innovation

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A B S T R A C T

Rapid economic development usually leads to serious environmental pollution problems. In order to solve the problem of pollutant emission in sustainable industrial development, it is urgent to examine the implementation effect of emissions trading policy (ETP) and its impact on green industrial development. This study adopts China's ETP as a case study and selects provincial panel data from 2004 to 2018. We first use a non-radial, non-directed, slack-based measure-directional distance function (SBM-DDF) to measure industrial green innovation efficiency. Then we use a difference in differences (DID) model to empirically test the emissions reduction effect of China's policy and whether it promotes industrial green innovation. Thereafter, results show that: (1) the ETP reduces sulfur dioxide (SO_2) emissions indicating the effectiveness of the policy; (2) the policy significantly improves industrial green innovation efficiency, meaning it promotes the sustainable development of the economy; (3) heterogeneity analysis highlights that ETP produces greater benefits for the most polluted regions of China which have more strict environmental regulations. The study examines the effect of emissions trading policy implementation from a new perspective. The study also provides a reference point for China to further refine its policy mechanisms and for other countries to formulate suitable ETP.

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1. Introduction

Over the past few decades, the global economy has been growing rapidly, however this growth has also changed the ecological environment of the planet. In particular, China is now facing serious environmental problems (Ning et al., 2020). Therefore, industrial development must be transformed from the traditional high consumption production model (with its corresponding high levels of pollution) to a more sustainable development model (Zhu et al., 2019; Chen et al., 2020). In this context, green innovation is crucial to facilitate high-performance sustainable economic development (Beise and Rennings, 2005; Borghesi et al., 2015). Green innovation encompasses sustainable innovation, ecological innovation, and environmental innovation. It relates to innovation activities focused on supporting environmental protection and sustainable development (Rennings, 2000). Furthermore, green innovation efficiency (GIE) a reflection of the input and output efficiency (Li and Zeng, 2020). In order to control environmental pollution, emissions trading is widely used in countries such as the United States, Canada, China and Japan (Calel and Dechezleprêtre, 2016; Zhang et al., 2018; Zhou et al., 2019).

As a paradigm of market-based incentive regulation, emissions trading policy (ETP) are of great significance for both environmental protection and sustainable development (Tang et al., 2020). Indeed, US economist Dales (1968) first proposed the theory of emissions trading, which was subsequently adopted by the US Environmental Protection Agency (EPA) to enable protection of the environment. In this context, emissions trading generates economic incentives through market mechanisms, which stimulate companies to adopt innovative technologies and processes to reduce emissions and realize sustainable development (Jaraite and Maria, 2012; Bel and Joseph, 2018; Zhou et al., 2019). However, due to the influence of a variety of factors, the issue of whether implementation of environmental regulation policies can promote economic growth while protecting the environment has become an important matter to be addressed. Consequently, the impact of environmental regulation on green innovation has become a major concern for various scholars (Jin et al., 2019; Zhang et al., 2019).

However, at present, the existing emissions trading policy research lacks the effect evaluation from the perspective of industrial green innovation efficiency. Also, the effect evaluation that is currently available mainly focuses on the environmental effect evaluation with there being less consideration of economic effect evaluation (Jaraite and Maria, 2012; Calel and Dechezleprêtre, 2016; Zhang et al., 2019; Xuan et al., 2020). Whereas other studies examine the impact of the emissions trading system on innovation patents and corporate performance (Calel and Dechezleprêtre, 2016; Marin et al., 2017). In addition, there are three contradictory viewpoints on the effect evaluation of the existing emissions trading policy, which are as follow: promotion (Zhang et al., 2018; Zhu et al., 2020; Lv et al., 2020), inhibition (Feng et al., 2018; Tang et al., 2020) and non-linearity (Wang and Shen, 2016; Li and Zeng, 2020). Moreover, there has been no exploratory research into the effectiveness of ETP, and no evaluation framework has been developed to determine the effectiveness of ETP from the perspective of industrial green innovation efficiency.

Therefore, the objective of this research study is to test not only the emission reduction effect of emissions trading policy but also the impact of this policy on the industrial green innovation efficiency. In order to address the objective, this study adopts China's emissions trading policy in 2007 and selects the inter-provincial panel data from 2004 to 2018. The study also uses the difference in differences (DID) model to empirically test the panel data. The study expands the application of the knowledge production function (Griliches, 1979; Jaffe, 1989) and incorporates ETP into an innovation input-output framework. As a consequence of the examination of environmental and economic effects in this study, relevant research on emissions trading theory is further enriched to verify that the emissions trading policy not only has the effect of emission reduction but also promotes the industrial green innovation efficiency and enriches the application of emission trading theory at the international level.

2. Literature review

2.1. Emissions trading policy

Industrial development and the resulting economic growth invariably create pollution problems (Munasinghe, 1999). In order to address the negative externality of environmental pollution, many regions have adopted environmental regulation (ER) (Zhao et al., 2014; Zhou et al., 2019). For example, Song et al., (2020a) tested the direct and the indirect impacts of environmental regulations on environmental pollution. Song et al. (2020b) found that the environmental policy of expanding prevention and control areas could effectively improve air quality. Externality refers to the external effect of an economic entity on another economic entity. Externalities can be positive or negative. The Coase Theorem (Coase, 1960) provides one way of solving negative externalities. According to this theorem, external economic problems are caused by unclear definitions of property rights and hence negative environmental externalities can be potentially eliminated through the effect of market transactions – with zero transaction costs and a clear definition of property rights, the market's spontaneity will automatically adjust resources to become Pareto optimal and optimally allocate resources.

A specific application of ER is air pollution control (Yang et al., 2016). ETP have been mainly studied from three perspectives: initial allocation (Woerdman, 2000; Ellerman and Buchner, 2007; Wråke et al., 2010; Betz et al., 2010), pricing (Coggins and Swinton, 1996; Fischer, 2008), and implementation (Bleischwitz et al., 2007; Jaraite and Maria, 2012; Shin, 2013; Marin et al., 2017). The present study focuses on the latter.

Studies of the effects of ETP mainly focus on environmental and economic aspects. Martin et al. (2015), for example, investigated the impact of the EU Emissions Trading Scheme (EU ETS) from the perspectives of emission reduction, innovation, competitiveness, and economic performance. The main goal of the EU ETS is to reduce emissions, with a further long-term goal being to stimulate innovation, and many studies have evaluated the emission reduction effect of the EU ETS (Bleischwitz et al., 2007; Sandoff and Schaad, 2009; Anderson and Maria, 2011; Jaraite and Maria, 2012; Zhang et al., 2019; Xuan et al., 2020; Ren et al., 2020). For example, Yan et al. (2020) studied the impact of China's carbon emissions trading policy on the environment and examined the collaborative governance effects of EST on air pollution from three aspects, namely haze, industrial SO_2 and industrial smog.

Other studies not only focus on the effects of the EU ETS on emission reduction, but also on the performance of the overall economy. Calel and Dechezleprêtre (2016), for instance, found that the EU ETS promoted an increase in low-carbon innovation patent applications. Anger and Oberndorfer (2008) studied the impact of the ETS on the performance of German companies and found that it had no obvious impact on company incomes and employment. Whereas Marin et al. (2017) employed propensity score matching (PSM) and DID to test the effect on the economic performance of companies, finding that ETS could improve turnover, mark-up, investment intensity, and labor productivity. Furthermore, Zhu et al. (2020) used the DID method to examine the impact of carbon emissions trading policy on the green development efficiency. Yang et al. (2020) found that China's carbon emissions trading policy expands the scale of employment while reducing emissions, achieving double dividends and the Porter effect. Zhang et al. (2020) studied the impact of emissions trading policy on the trading market efficiency and found that this policy promoted economic growth while reducing emissions. In other work, Tang et al. (2020) conducted an analysis of the impact of China's emissions trading system on innovation and productivity and found that although the ETP promoted innovation, it had no impact on productivity. Moreover, Shin (2013) concluded that China's pilot areas did not institutionalize SO_2 emissions trading and that the overall policy was unsuccessful.

2.2. Green innovation efficiency

As a consequence of increasingly severe environmental problems, green innovation efficiency, which is regarded as the embodiment of innovation factors and resource utilization efficiency (Du et al., 2019), has become a highly topical research area. This is based on the need to take environmental factors into consideration – reflecting the efficiency of green innovation input and output, and thereby effectively measuring the green innovation process of industrial companies (Li and Zeng, 2020).

Current research in this area mainly focuses on the measurement of green innovation efficiency (Cheng and Yin, 2016; Du et al., 2019; Li and Zeng, 2020) and the influencing factors involved (De Vries and Withagen, 2005; Demirel and Kesidou, 2011; Triguero et al., 2013; Borghesi et al., 2015).

In terms of the measurement method and data selection, Li and Zeng (2020) used a super-slack-based model (SBM) to measure the green innovation efficiency of some highly pollutant industries in China from 2011 to 2015. Du et al. (2019) examined data from 2009 to 2016 and used a two-stage network DEA model to measure and analyze the differences in green innovation efficiency of regional industrial companies in 30 provinces. Cheng and Yin (2016) used the data envelopment analysis (DEA) model and found that although green innovation efficiency was growing in 30 provinces during 2008–2013, the growth is at significantly different interregional rates. Zhang et al. (2020) used the SBM-DDF model to calculate green innovation efficiency for the city of Xi'an in China during 2003–2016. Whereas Zhu et al. (2020) used the super-efficiency SBM model to measure the green development efficiency in 30 provinces in China.

Meng et al. (2016) systematically reviewed the literature on regional energy and carbon emission efficiency (EE&CE) research from the aspects of application attribute, variable scheme, model aspect, and analyzed the differences in the calculation results of six different DEA models. Moreover, Meng et al. (2019) studied the ranking reversal phenomenon of China's regional energy efficiency under different DEA models (namely Radial, M-Radial, SBMT, RAM and DDF model).

In terms of variable index selection, Li and Zeng (2020) adopted R&D personnel, R&D input and industrial energy consumption as input indexes, and the output index selected effective invention patents per hundred million yuan of income and industrial solid pollution utilization rate. Zhang et al. (2020) used labor, capital and resource inputs as input indexes, and output was GDP, green output, and non-expected output was SO_2 emissions. In other work, Feng et al. (2018) primarily included the inputs of labor, capital and energy. The expected output is the number of patents and sales revenue of new products, while the non-expected output is the discharge of industrial waste water, waste gas and solid waste. To sum up, the existing research is mainly aimed at investigating 30 provinces in China and the DEA model is has been widely used, where the measurement indexes are mostly input, output and non-expected output.

For the studies on the influencing factors, Borghesi et al. (2015) investigated the link between the EU ETS and environmental innovations. De Vries and Withagen (2005) studied the influence of the stringency of European SO_2 emissions, environmental policy, and innovativeness from 1970 to 2000, finding that strict environmental policy stimulated innovation. While Demirel and Kesidou (2011) used data from UK industrial companies to investigate the effect of policy and company factors on different types of eco-innovations. Tang et al. (2020) used both a DID model and a difference-in-difference-in-differences (DDD) model to test the effect of command-and-control regulation on green innovation efficiency. Whereas Huang et al. (2016) studied the impact of regulators on green innovation performance. Furthermore, many studies have investigated the impact of environmental regulation on green innovation, which has also become a recent priority research area (Huang et al., 2016; Chen et al., 2017; Wang et al., 2020).

2.3. Relationship between ETP and green innovation efficiency

There has been a large number of studies into the effect of environmental regulation. Cecere and Corrocher (2016), for instance, found that strict environmental regulations have a stronger influence on innovation. Other studies (Yabar et al., 2013; Zhang et al., 2018L. Zhang, 2018; Y. Zhang, 2018) found that ER can improve technological innovation. Indeed, many also believe that ER can promote green innovation (De Vries and Withagen, 2005; Zhao and Sun, 2016; Wang et al., 2020). At present, there are mainly three viewpoints on this matter, which are inhibition, promotion and non-linearity.

The first view is that environmental regulations have an inhibitory effect. According to neoclassical economics, environmental regulation can promote environmental protection but also leads to additional costs for companies, which will further lead to a reduction in international competitiveness and become detrimental to economic growth (Cecere and Corrocher, 2016; Xie et al., 2017). For example, You et al. (2019) found that, under the influence of fiscal decentralization and political competition, environmental regulation cannot promote green innovation. Feng et al. (2018) concluded that ER significantly inhibits green innovation efficiency in the manufacturing industry. Further, Tang et al. (2020) found that command-control regulation can inhibit companies' green innovation efficiency. Whereas Blind (2012) argued that ER has a negative effect on innovation performance, while Shi et al. (2018) found that China's Emissions Trading Pilot significantly inhibits industrial innovation.

The second view is that there is a promoting effect. Although Porter and Linde (1995) put forward an alternative view, in that legitimate and strict ER can actually inspire companies to invest more in innovative activities to enhance competitiveness, thus reducing the additional environmental costs of companies and creating a win-win situation between the environment and the economy. Scholars have found that market-based incentive regulation has a greater influence on emission reduction and green innovation (Requate, 2005; van den Bergh et al., 2011). Zhao et al. (2014), for instance, explored different types of environmental regulation (i.e. command-control and market-based) – proposing that market-based incentive regulation is more conducive to the transformation to a green development strategy. Lv et al. (2020) identified that strict environmental regulation promotes corporate innovation, whereas loose environmental regulation can reduce company innovation and lead to an increase in the number of environmental related patents. Zhang et al. (2018) found that ETP can promote companies' green innovation. Whereas Zhu et al. (2020) found that China's carbon emissions trading policy promotes green development efficiency.

The third view is that some scholars believe that the relationship between ER and green innovation is not only a simple linear relationship, but a nonlinear relationship. Li and Zeng (2020) employed regression analysis and found a U-shaped relationship between environmental regulation and green innovation efficiency. Whereas Wang and Shen (2016) first calculated environmental productivity through the GML index and studied the impact of environmental regulations on it. The study found an inverted U-shaped relationship between the two. Shen et al. (2019) studied the nonlinear effects of different types of environmental regulations on environmental total factor productivity (ETFP), and identified that in light-polluting industries, market-incentive environmental regulations have an N-type relationship with green total factor productivity. Zheng et al. (2020) also found that there is a U-shaped relationship between environmental regulation and economic efficiency.

2.4. Knowledge gap

The above review of the literature reveals two clear knowledge gaps, which are summarized as follows.

(1) *There is a lack of research into industrial green innovation efficiency as a policy effect.*

Despite environmental factors having become the focus of research into traditional innovation efficiency, there is still limited research into green innovation efficiency. Most research into the effects of environmental regulation are focused on developed countries and fails to distinguish between different forms of environmental regulations. Existing research focuses on the effects of emission reduction, including the economic effects represented by patents, but rarely examines the effects of environmental regulation. The use of specific environmental regulations to test the effect of green innovation efficiency can produce more accurate assessments, which are helpful for enriching environmental regulation policy theory.

(2) *There is a need for further verification of the effect of specific environmental regulations.*

The conclusions from research into the impact of environmental regulation are presently mixed, since promotion, inhibition and non-linear relationships have all been identified. An important issue is to understand the impact of the ETP as a typical policy of market-based incentive environmental regulation. Also, there is a need to further study the extent to which emissions trading policy can achieve emissions reduction and promote industrial green innovation under the dual pressure of economic growth and environmental protection. Further research into ETP can help to better evaluate the effects of these policies and test Porter's Hypothesis (Mohr, 2002).

3. Methodology

It is assumed that innovation input is the main explanatory variable of innovation output in our data envelopment analysis (DEA) model. According to the production function model of the R&D input and output relationship proposed by Griliches (1979) and Jaffe (1989), and based on the “Cobb-Douglas” function, the regional province and city innovation efficiency function are:

$$innov_i = A_i(input_i)^{\beta} \tag{1}$$

where $innov_i$ denotes the innovation efficiency of provinces; i is a Chinese province; A is the coefficient of input; $input_i$ is the input of provincial innovation, mainly the impact of innovation efficiency but including environmental regulation and specific environmental policy; β is the output elasticity of the city's innovative input. Factors such as economic development level, foreign direct investment (FDI), education level, industrial scale, and industrial structure are also included.

3.1. Difference in differences (DID)

According to the literature, the main method used for evaluating policy effectiveness is regression discontinuity (Thistlethwaite and Campbell, 1960), instrumental variables (Ehrlich, 1975), propensity score matching (Rosenbaum and Rubin, 1983), and difference in differences (Ashenfelter and Card, 1985). Ashenfelter and Card (1985) first evaluated the policy effect using the DID method. This is now widely used to evaluate policy effectiveness (Yang et al., 2020; K. Tang et al., 2020) by testing the effect of policy before and after the implementation of the treatment group (i.e. policy adoption areas) and control group (i.e. where the policy is not adopted). DID allows for, and accommodates, the existence of unobservable factors to influence whether an individual accepts an intervention decision. Relaxing the conditions of policy effectiveness, evaluation allows the application of policy assessment to be closer to economic reality, and hence more representative (Zhang et al., 2019; Yang et al., 2020).

DID mainly considers two dummy variables: the time variable, dt, and the policy variable, du. $dt = 0$ when the time is before policy adoption and $dt = 1$ when the time is after. du $= 0$ denotes the area where the policy is not adopted (i.e. the control group) and du $= 1$ denotes the pilot area of the policy (i.e. treatment group). The DID model is (Abadie and Cattaneo, 2018; Zhou et al., 2019):

$$Y_{it} = \beta_0 + \beta_1 du + \beta_2 dt + \beta_3 du{*}dt + \varepsilon_{it} \tag{2}$$

where $du \times dt$ is the time and policy interaction term, and its coefficient β_3 reflects the effect of the policy. As shown in Table 1, substituting values into (1) and (2) enables the result of the two differences, β_3, to be obtained – the measure of the effect of the policy.

For example, DID is used here to evaluate the effectiveness of China's ETP in 2007. Therefore, the pilot provinces of the policy are deemed “treatment groups”, and the provinces that have not adopted the ETP are considered “control groups”. In order to solve the endogeneity problem caused by missing variables, control variables based on (2) are included to give

$$Y_{it} = \beta_0 + \beta_1 D_i{*}T_t + \beta_2 Z_{it} + \lambda_t + \mu_i + \varepsilon_{it} \tag{3}$$

where the subscripts i and t denote the province and year respectively, and the independent variable Y is the natural logarithm of the industrial SO_2 emissions and industrial green innovation efficiency respectively. D is the policy dummy, being 1 for the provinces that adopt the ETP, and 0 otherwise. T is a time dummy, being 1 for the time after policy adoption (2007), and 0 otherwise. $D \times T$ is the interaction of the policy variable and time variable. The purpose of coefficient β_1 is to evaluate policy effectiveness. An estimated result of $\beta_1 > 0$ indicates that the ETP has a positive effect on the dependent variable Y, otherwise it has a negative effect on Y. ε is the random disturbance term of the model. Z is the control variable. λ_t is the time-fixed effect, and μ_i is the regional fixed effect.

Table 1
Parameter meaning of each variable in DID model.

	The year before the control period ($dt = 0$)	The year after the control period ($dt = 1$)	Difference
Pilot areas (Treatment group, $du = 1$)	$\beta_0+\beta_1$	$\beta_0+\beta_1+\beta_2+\beta_3$	$\beta_2+\beta_3$
Non-pilot areas (Control group, $du = 0$)	β_0	$\beta_0+\beta_2$	β_2
Difference	β_1	$\beta_1+\beta_3$	$\Delta\Delta d = \beta_3$ (DID)

3.2. Slack-based measure-directional distance function (SBM-DDF)

Data envelopment analysis (DEA) can be used to calculate the efficiency of multiple inputs and multiple outputs (Zhang et al., 2020; Zhang et al., 2020; Meng et al., 2016). The earliest CCR model was used to determine efficiency by analyzing input and output data (Charnes et al., 1978). Thereafter Banker et al. (1984) proposed the classic BCC model. Radial models, such as CCR and BCC, which are widely used (Meng et al., 2019).

Initially, the environment and resources are taken as inputs (Reinhard et al., 1999). With the intensification of economic and resource conflicts, Chung et al. (1997) proposed the directional distance function (DDF) model with environmental pollution as an unexpected output. However, the traditional directional distance function has radial and directivity of input and output, when there is excessive input or insufficient output which leads to deviations from the true efficiency value.

In order to solve the problem of slack variables, Tone (2001) proposed a non-radial, non-oriented Slacks Based Measure (SBM) model to solve the problem of increasing or decreasing the proportion of input and output and it can be observed that SBM and DDF models have gradually become popular with researchers (Meng et al., 2016). Therefore, Fukuyama and Weber (2009) combined SBM and DDF to obtain a non-radial, non-directed Slack-based measure-directional distance function (SBM-DDF), which not only avoided calculation distortion but also overestimated the efficiency when the DDF model had slack variables. This approach also treats environmental pollution as an undesired output. which can measure efficiency more realistically. Consequently, the SBM-DDF methodology has been employed to measure industrial green innovation efficiency (Zhang et al., 2020).

In this research study, each province and city in China is a decision-making unit (DMU). x is the N inputs of the decision-making unit, $x=(x_1, \ldots = x_N) \in R^* N$; y is the M expected outputs, $y=(y_1, \ldots = y_M) \in R^* M$; b is K unexpected outputs, $b=(b_1, \ldots = b_K) \in R^* K$; $(xt\,i, yt\,i, bt\,i)$ is the input-output data of the ith region in period t, (g^x, g^y, g^b) is the direction vector, (S_n^x, S_m^y, S_k^b) is the slack vector of input and output. Hence, the model is defined as

$$\vec{S^t} = \left(x_i,\ y_i,\ b_i, g^x, g^y, g^b\right) = \frac{1}{3}\max\left(\frac{1}{N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x} + \frac{1}{M}\sum_{m=1}^{M}\frac{s_m^y}{g_m^y} + \frac{1}{K}\sum_{k=1}^{K}\frac{s_k^b}{g_k^b}\right) \tag{4}$$

$$s.t\ x_{in} = \sum_{i=1}^{I} x_{in}\lambda_i + s_n^x,\ \forall n;\ y_{im} = \sum_{i=1}^{I} y_{im}\lambda_i - s_m^y,\ \forall m;$$

$$b_{ik} = \sum_{i=1}^{I} b_{ik}\lambda_i + s_k^b,\ \forall k;$$

$$\lambda_i \ge 0, \sum_{i=1}^{I}\lambda_i\ = 1,\ \forall i;\ s_n^x \ge 0,\ \forall n;\ s_m^y \ge 0, \forall m; s_k^b \ge 0,\ \forall k$$

In order to solve expression (4) with linear programming methods, we obtain the efficiency index, measured as the inverse of green innovation efficiency – the larger the value, the lower the green innovation efficiency. When the direction vector $g_n^x = x_n^{max} - x_n^{min}$, ∀n and $g_m^y = y_m^{max} - y_m^{min}$, ∀m, the green innovation efficiency (GIE) is

$$\vec{GIE} = 1 - \vec{S^t} = \left(x_i, y_i,\ b_i, g^x, g^y, g^b\right) \tag{5}$$

$$\text{s.t}\ g_n^x = x_n^{max} - x_n^{min},\ \forall n;\ g_m^y = y_m^{max} - y_m^{min},\ \forall m; g_k^b = x_k^{max} - x_k^{min},\ \forall k$$

Since the inefficiency value $\vec{S^t}$ remains between 0 and 1, the GIE value also remains between 0 and 1. Therefore, the larger the value is, the larger will be green innovation efficiency.

3.3. Variables and data

The effect of the ETP adoption in the year 2007 is evaluated from two perspectives. The first is to test ETP effectiveness (i.e. its emissions reduction effect). The second is through measuring the effect on industrial green innovation efficiency. Since the ETP mostly targets industrial companies, industrial SO_2 emissions is adopted as the control variable.

The variables involved in this research include dependent variables, an independent variable, and the specified control variables. The dependent variables are industrial SO_2 emissions and industrial green innovation efficiency. The independent variable is the dummy time and policy interaction term. The control variables are economic development level, foreign direct investment, education level, industrial scale, and industrial structure. The selection and meaning of each variable is explained below.

One of the dependent variables is green innovation efficiency. As mentioned earlier, SBM-DDF is used to measure industrial green innovation efficiency and input and output indicators are selected with reference to common practices. The

Table 2
Variables definition table.

	Variables name	Variables symbol	Variables definition	References
Input indicators	Human input	L	Full-time equivalent of R&D personnel	Cheng and Yin (2016), Du et al. (2019), Zhu et al. (2019), Li and Zeng (2020)
	Capital investment	K	Expenditure on R&D	Cheng and Yin (2016), Du et al. (2019), Zhu et al. (2019), Li and Zeng (2020)
Output indicators	Expected output	G	Sales revenue of new products	Cheng and Yin (2016), Du et al. (2019), Wang and Shao (2019), Zhu et al. (2019)
		P	Number of patent applications	Cheng and Yin (2016), Du et al. (2019), Zhu et al. (2019)
	Unexpected output	E	Industrial SO_2 emissions	Cheng and Yin (2016), Du et al. (2019), Jin et al. (2019), Xie et al. (2017), Zhu et al. (2019)
Control variables	Economic development level	GDP	Natural logarithm of GDP per capita	Wang and Shao (2019)
	Foreign direct investment	FDI	Ratio of the amount of foreign investment to GDP	Wang and Shao (2019), Zhu et al. (2019)
	Education level	EDU	The proportion spend on education in national budget expenditure	Jin et al. (2019)
	Industrial scale	SIZE	Ratio of the gross output value to the number of industrial companies	Xie et al. (2017)
	Industrial structure	IS	The proportion of the output value of the secondary industry to the GDP	Jin et al. (2019), Yang et al. (2020)

data are from designated industrial companies.[1] The input indicators are divided into human input and capital investment. Here human input (L) is represented by the full-time equivalent of R&D personnel, and capital investment (K) is represented by expenditure on R&D. The output indicators are divided into expected output and unexpected output. Expected output is represented by the number of patent applications (P) and the sales revenue of new products (G). The unexpected output is industrial SO_2 emissions.

The specific control variables are as follows:

(1) Economic Development Level – Gross Domestic Product (GDP). GDP affects green innovation efficiency, and areas with high economic development are expected to attach importance to innovation. Thus, the value is represented by the natural logarithm of GDP per capita.
(2) Foreign Direct Investment (FDI). FDI provides improved innovative technologies and resources, and the competitive effect also leads to companies paying more attention to innovation. Therefore, FDI is represented by the ratio of the amount of foreign investment to GDP.
(3) Education Level (EDU). New Economic Growth theory holds that human capital is the main driving force behind economic growth. As a consequence of improving the education level, it is easier to absorb new knowledge and technology, which is conducive to industrial green innovation. Therefore, EDU is represented by the proportion spent on education in national budget expenditure.
(4) Industrial Scale (IS). Green innovation efficiency can vary according to different industrial scales. For example, large companies are more willing to invest more resources into promoting industrial green innovation efficiency. Therefore, the value is represented by the ratio of industrial gross output value to the number of industrial companies.
(5) Industrial Structure (IS). The emission intensity of the secondary industry is higher than other industries and therefore the proportion of different (secondary or primary/tertiary) industries may have different effects. The proportion of the output value of the secondary industry to GDP is used to represent the value.

More details relating to all the variables are provided in Table 2.

3.4. Data selection

As early as 1987, there was emissions trading taking place between companies in Shanghai. In 2002, the former State Environmental Protection Administration of China selected seven provinces (namely Shanxi, Shandong, Jiangsu, Shanghai, Henan, Liuzhou, and Tianjin) and China Huaneng to conduct pilot scale projects for SO_2 emissions trading. In 2007, 11 provinces (namely Tianjin, Jiangsu, Hubei, Zhejiang, Inner Mongolia, Hunan, Chongqing, Shanxi, Shaanxi, Henan, and Hebei) also adopted pilot scale emissions trading (Shin, 2013).

As the ETP adopted in 2007 was more comprehensive than the 2002 version of the policy, the scale and scope of emissions trading have also been expanded and trading activity has become more active. The 2007 ETP is therefore selected to empirically evaluate ETP effectiveness. Due to data collection restrictions, panel data is selected from a total of 30 provinces (see Table 3).

All the data are from the *China Statistical Yearbook* (2005–2019) (China, 2005a-2019a) and *China Statistical Yearbook* on Science and Technology (2005–2019) (China, 2005b-2019b). The selected timeframe is 2004–2018. In order to eliminate price fluctuations, the producer price indices for industrial products provided in the *China Statistical Yearbook* are used to rebase the gross output value of industry to the 2003 level (Zhou et al., 2019). Similarly, the per capita gross regional product indices are used to adjust per capita gross regional product values. Based on the exchange rate provided in the China Statistical Yearbook, USD values are converted into the CNY equivalent.

Table 4 provides descriptive statistics of the variables, including their arithmetic means and standard deviations (SD).

Table 3
Specific grouping situation.

Group	Treatment group (policy implementation)	Control group (policy not implemented)
Provinces	Jiangsu, Zhejiang, Tianjin, Hubei, Hunan, Inner Mongolia, Shanxi, Chongqing, Shaanxi, Hebei, Henan	Liaoning, Jilin, Heilongjiang, Anhui, Jiangxi, Fujian, Shandong, Guangdong, Guangxi, Sichuan, Yunnan, Beijing, Shanghai, Hainan, Qinghai, Guizhou, Xinjiang, Gansu, Ningxia

[1] According to the China Statistical Yearbook, the scope of industrial enterprises above a designated size are: all state-owned industrial enterprises and the non-state-owned industrial enterprises with revenue from their principal business over CNY 5 million from 2004 to 2006; all industrial enterprises with revenue from their principal business over CNY 5 million from 2007 to 2010; and all industrial enterprises with revenue from their principal business above CNY 20 million since 2011.

Table 4
Descriptive statistics of specific variables.

	All the samples				
Variables	Obs.	Mean	Std. dev.	Min	Max
GIE	450	0.81141	0.12435	0.52646	1
LN SO_2	450	3.71414	0.94875	0.18232	5.1504
D × T	450	0.29333	0.4558	0	1
GDP	450	9.50382	0.5045	8.24748	10.8894
FDI	450	0.02629	0.01893	0.0001	0.10413
EDU	450	0.16192	0.026	0.09895	0.22217
SIZE	450	1.85657	1.07022	0.4313	5.9972
IS	450	0.44579	0.1093	0.00366	0.67232

4. Results

The effect of the ETP is evaluated through the following steps: (1) Plotting the time trend of the industrial green innovation efficiency of the treatment and control group, and observation of the changing trends of the two groups; (2) Empirical testing using the DID model; (3) Robustness checks; and (4) Heterogeneity analysis.

4.1. Time trend graph of industrial green innovation efficiency

The difference between the two groups regarding industrial green innovation efficiency (Winsorized to eliminate the influence of outliers on the estimation results) is presented visually in Fig. 1. This shows that, before 2007, the industrial green innovation efficiency trends of the treatment and control groups were parallel. However, after 2007, green innovation efficiency (GIE) improved for both groups of provinces, but more for the treatment group, thereby suggesting a potential causal relationship with the ETP adopted in 2007. However, statistical analysis is needed to determine the specific effects involved.

4.2. Regression analysis

(1) *ETP effectiveness*

A two-way fixed effects model, comprising the time effect and individual effect, is used to conduct the empirical tests (Zhang et al., 2019). The prerequisite for studying the relationship between the ETP and industrial green innovation efficiency is the ETP's effectiveness. Firstly, according to model (3), the natural logarithm of industrial SO_2 emissions (LN SO_2) is selected as the dependent variable.

The emissions reduction effect is examined by gradually incorporating other control variables into the model (namely GDP, FDI, EDU, SIZE, IS). Table 5 summarizes the results, showing that the significance of the coefficients and symbols of the variables do not change with the addition of the control variables, thereby indicating that the results are quite robust. With the gradual addition of control variables (GDP, FDI, EDU, SIZE, IS), the coefficient of the interaction term becomes significantly negative and is stable near −0.17.

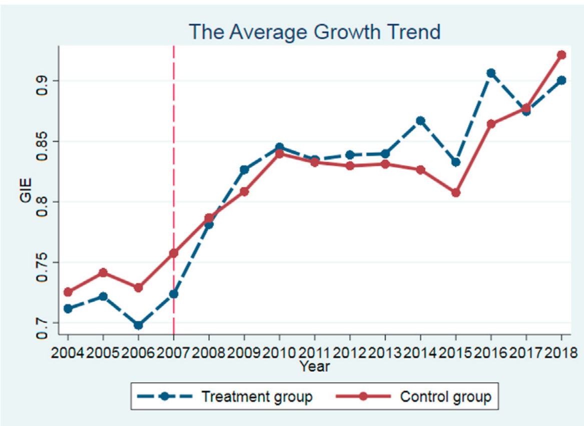

Fig. 1. Time trend graph.

Table 5
Examination of the effectiveness of emissions trading policy.

VARIABLES	(1) LN SO_2	(2) LN SO_2	(3) LN SO_2	(4) LN SO_2	(5) LN SO_2	(6) LN SO_2
D × T	−0.1741***	−0.1668***	−0.1662***	−0.1757***	−0.1739***	−0.1722***
	(0.0638)	(0.0636)	(0.0637)	(0.0640)	(0.0616)	(0.0617)
GDP		0.4802**	0.4954**	0.5259**	0.5845**	0.6576**
		(0.2345)	(0.2359)	(0.2368)	(0.2280)	(0.2547)
FDI			−0.7614	−0.7238	−2.1414*	−2.0571*
			(1.1648)	(1.1642)	(1.1459)	(1.1541)
EDU				1.6049	1.8154	1.8596
				(1.2383)	(1.1914)	(1.1942)
SIZE					−0.1550***	−0.1553***
					(0.0267)	(0.0267)
IS						−0.1822
						(0.2825)
Constant	3.8859***	−0.5717	−0.6882	−1.2137	−1.6270	−2.2348
	(0.0476)	(2.1779)	(2.1867)	(2.2222)	(2.1382)	(2.3381)
Provinces fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES	YES	YES
Observations	450	450	450	450	450	450
R-squared	0.7833	0.7855	0.7857	0.7866	0.8031	0.8033
Number of provinces	30	30	30	30	30	30

Note: Standard errors in parentheses; ***, **, * indicates statistical significance at 1%, 5% and 10% level, respectively; Year indicates time fixed effect, and Province indicates individual fixed effect.

Table 6
Effect of emissions trading policy on industrial green innovation efficiency.

VARIABLES	(1) GIE	(2) GIE	(3) GIE	(4) GIE	(5) GIE	(6) GIE
D × T	0.0284*	0.0286*	0.0278*	0.0306*	0.0312**	0.0306**
	(0.0160)	(0.0160)	(0.0158)	(0.0159)	(0.0150)	(0.0150)
GDP		0.0110	−0.0101	−0.0193	−0.0024	−0.0276
		(0.0591)	(0.0585)	(0.0586)	(0.0556)	(0.0621)
FDI			1.0591***	1.0477***	0.6384**	0.6093**
			(0.2887)	(0.2883)	(0.2794)	(0.2813)
EDU				−0.4848	−0.4240	−0.4393
				(0.3066)	(0.2905)	(0.2910)
SIZE					−0.0448***	−0.0447***
					(0.0065)	(0.0065)
IS						0.0629
						(0.0688)
Constant	0.7146***	0.6123	0.7744	0.9331*	0.8137	1.0235*
	(0.0119)	(0.5485)	(0.5420)	(0.5502)	(0.5214)	(0.5698)
Provinces fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES	YES	YES
Observations	450	450	450	450	450	450
R-squared	0.4806	0.4806	0.4974	0.5005	0.5531	0.5541
Number of provinces	30	30	30	30	30	30

Note: Standard errors in parentheses; ***, **, * indicates statistical significance at 1%, 5% and 10% level, respectively; Year indicates time fixed effect, and Province indicates individual fixed effect.

(2) *The ETP's impact on industrial green innovation efficiency*

Table 6 shows the results for the impact of the ETP on the industrial green innovation efficiency model by gradually adding the control variables GDP, FDI, EDU, SIZE, and IS. Again, the significance of the coefficients and symbol of the variables do not change with the addition of the control variables, indicating that the results are still robust. However, the interaction term is always significantly positive and basically stable near 0.03.

4.3. Robustness checks

In order to ensure the robustness of the results, robustness checks have been conducted according to the following three perspectives.

Table 7
Robustness checks.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	GIE	GIE	GIE	GIE	GIE	GIE
D × T1	−0.0169	−0.0148				
	(0.0258)	(0.0241)				
D × T2	−0.0262	−0.0289				
	(0.0258)	(0.0241)				
D × T3	−0.0422	−0.0484**				
	(0.0258)	(0.0243)				
D × T			−0.0100	−0.0157	0.0052	0.0164
			(0.0169)	(0.0168)	(0.0160)	(0.0153)
Constant	0.7208***	1.0326*	0.7146***	1.6569	0.7146***	1.0426*
	(0.0152)	(0.5707)	(0.0089)	(1.5338)	(0.0120)	(0.5723)
Control variables	NO	YES	NO	YES	NO	YES
Provinces fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES	YES	YES
Observations	450	450	150	150	450	450
R-squared	0.4812	0.5553	0.2640	0.3237	0.4766	0.5508
Number of provinces	30	30	30	30	30	30

Note: Standard errors in parentheses; ***, **, * indicates statistical significance at 1%, 5% and 10% level, respectively.

(1) *"Parallel paths" assumption*

The DID method can solve the endogeneity problem caused by the factors that do not change with time, and eliminate the influence of unobserved confounding factors. However, DID requires that the GIE of the two groups maintain basically parallel paths before implementation of the policy, that is, the most essential condition for using DID is the "parallel paths" assumption (Zhang et al., 2019). Before 2007, the two groups in Fig. 1 were basically parallel, and the parallel paths were initially verified. On this basis, the study introduces the parallel paths test of the interaction items (D × T1, D × T2, D × T3) of the time dummy variables in the years before 2007 and the policy dummy variable. If the interaction term is not significant, it indicates that the two groups are not significantly different before the policy implementation. Model (1) and model (2) in Table 7 are without control variables and with control variables added, respectively. The results show that although the interaction term D × T3 is significant, the three interaction items are still not significant. Therefore, it can be observed that the empirical result conforms to the "parallel paths" assumption. That is, before the implementation of emissions trading policy there is not a significantly difference in the level of green innovation efficiency between the two groups.

(2) *Counterfactual test by changing the year of the treatment*

It can be observed that other policies or influencing factors may potentially impact the results of this research study. Therefore, the counterfactual test was carried out by changing the policy implementation time (Jiménez and Perdiguero, 2017; Yang et al., 2020). It is assumed that the policy implementation year is 2006, and the sample period selected is 2004–2008. In this regard, if the result of the interaction term coefficient is not significantly positive, then it is assumed that the improvement of industrial green innovation efficiency is due to the emissions trading policy implemented in 2007. Otherwise, it may be caused by other policies or factors. The results are shown in Table 7. Model (3) assumes that the policy implementation time is 2006 and does not add control variables; model (4) adds control variables based on model (3). The interaction term coefficient in Table 7 is not significant, indicating that the empirical result of this research is robust. That is to

Table 8
Heterogeneity analysis.

	(1) High pollution regions	(2) Low pollution regions	(3) Strict environmental regulation	(4) Tolerant environmental regulation
VARIABLES	GIE	GIE	GIE	GIE
D × T	0.0402**	−0.0073	0.0332*	0.0345
	(0.0185)	(0.0272)	(0.0196)	(0.0230)
Constant	0.5992	−0.4797	0.8278***	0.7849***
	(0.7173)	(0.9678)	(0.0548)	(0.0794)
Control	YES	YES	YES	YES
Provinces fixed effect	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES
Observations	225	225	225	225
R-squared	0.6317	0.5771	0.5657	0.6173
Number of provinces	15	15	15	15

Note: Standard errors in parentheses; ***, **, * indicates statistical significance at 1%, 5% and 10% level, respectively.

say, the improvement of the green innovation efficiency is caused by implementation of the emissions trading policy, not by other factors.

(3) *Randomly select pilot provinces*

In order to test whether the policy effect is caused by some unobservable factors, this study adopts a random selection of pilot provinces for the robustness test (Yang et al., 2020). If the test result is not significant, it means that the main results are reliable; otherwise, it indicates that there is a deviation in the regression results of the study. In this research, random sampling is used to select 11 provinces among 30 provinces as the treatment group and the rest of the provinces as the control group. Model (5) and model (6) in Table 7 are without control variables and with control variables added, respectively. The analysis highlights that the interaction term coefficient is not significant, indicating that the empirical result of this research is robust.

4.4. Heterogeneity analysis

Due to the differences in economic development of different Chinese provinces, there is more serious environmental pollution in the more industrialized regions. It is expected, therefore, that environmental regulation may have a more intensive effect in heavily polluted regions. Accordingly, the provinces are further divided into high and low pollution regions in relation to the median pollution emissions. Models (1) and (2) in Table 8 contain the results for the high and low pollution regions respectively, indicating that the ETP's effect is indeed better in high pollution regions. This is obviously because local governments in high pollution regions usually pay more attention to environmental treatment and are expected to adopt stricter environmental regulations. Additionally, high pollution regions are comparatively more developed and have higher levels of technological development, as it is also easier to promote R&D activities as well as green innovation efficiency.

The ETP's influence will also be related to institutional factors. This is because its effective adoption requires strict environmental supervision and implementation (Ren et al., 2020). The different environmental regulation intensities also lead to different ETP effects, the value of which is represented by the proportion of investment in the treatment of industrial pollution to GDP. The median of the data is used to divide the provinces into strict and tolerant environmental regulation regions. Models (3) and (4) in Table 8 show the results, which indicate that, as expected, the ETP in strict environmental regulation regions significantly improves industrial green innovation efficiency.

5. Discussion and policy implications

This study has generated a number of policy implications. Firstly, this research indicates that the ETP reduces industrial SO_2 emissions. Hence, China's emissions trading policy is effective and achieves the desired emissions reduction effect. This result is consistent with Zhang et al. (2019) and Zhou et al. (2019), where both studies found the emissions reduction effect to be associated with the ETP. This is because the emissions trading policy implements total quantity control, which limits the emission of pollution to a certain extent so as to achieve corporate emission reduction. However, Shin (2013) found that emission reductions had not been achieved. This is because the emissions trading policy is still at the initial stage of introduction, resulting in inactive secondary market transactions and low enthusiasm for corporate participation. Therefore, ETP it cannot effectively play the role of policy. Moreover, this study investigates industrial enterprises above a designated size, which are the main targets of the implementation of the policy and the main goal of emissions reduction. Consequently, it is easier to conclude that the implementation of emissions trading policy can reduce pollution emissions. This study provides direction for the government to deal with environmental pollution problems and help solve the current serious environmental pollution.

This study adopts the new perspective of green innovation efficiency to measure the economic effects of China's emissions trading policy, and enriches the application research of emissions trading theory at the international level. Multiple indicators are used to measure industrial green innovation efficiency more effectively. The results indicate that the ETP can improve industrial green innovation efficiency, which is similar to the findings of Zhu et al. (2020) and Zhang et al. (2018).

Companies with lower levels of pollution can obtain economic benefits by selling spare emissions capacity, which allows them to promote green innovation strategies. Conversely, companies with higher levels of pollution need to purchase spare emission capacity to meet their production emission needs. Therefore, although the emissions trading policy will increase the pollution cost of enterprises in the short term, in the long term, the economic compensation brought by the sale of excess emission rights will stimulate enterprises to improve pollution control technologies and increase the green innovation efficiency thereby offsetting the environmental costs of enterprises (Ren et al., 2020). Unlike the results of Tang et al. (2020), this is because the market-based ETP provide companies with greater flexibility in reducing emissions (Tang et al., 2020; Ren et al., 2020) and the ETP's environmental costs are lower than other forms of command-control environmental regulation. The research highlights that policy is not only conducive to promoting the transformation and upgrading of enterprises but also helps achieve high-quality economic development. It also reveals intuitively how the emissions trading policy plays a long-term role in China's pollution control and economic development, and provides an important reference for the Chinese government to establish environmental regulations that achieve a win-win situation for the environment and the economy.

This study further examines the heterogeneity in different polluted regions and different environmental regulation intensities and finds that the implementation of emissions trading policy is improved in areas with high pollution and strict environmental regulations. This result is consistent with the findings of Cecere and Corrocher (2016). On the one hand, the stronger the implementation of environmental regulations and the higher the cost of violations of the law, the lower the possibility of violations of the law, and the more effective the implementation of policy, as well as the realization of a win-win situation for the economy and the environment. On the other hand, this is because companies that operate under more strict environmental regulations tend to invest more capital in pollution-control technologies (De Vries and Withagen, 2005).

The following policy implications can be drawn from the aforementioned findings.

(1) Acknowledge the full role of the effects of market-based policies. It can be observed from this study that emissions trading policy reduces pollution emissions and improves the green innovation efficiency, thereby indicating that this policy can not only achieve the goal of reducing emissions but also promote the green development of the Chinese economy. Therefore, all government departments should pay appropriate attention to the implementation of this policy and acknowledge the effective role of the market in environmental governance as well as continue to promote China's market-oriented mechanism reform. On the one hand, it is necessary to continuously adjust the policy according to the implementation effect and the actual situation of the enterprise, and establish a standardized and effective trading market. On the other hand, there is also a concomitant need for cooperation between different areas, thereby actively promoting the development of cross-regional transactions, expanding the scope and scale of the adoption of emissions trading policy, reducing administrative interventions in the market, and allowing the flexibility and effectiveness of transactions (Zhou et al., 2019).
(2) Formulate different policies based on regional characteristics. This study finds that the implementation effect of the policy is different in the different regions of China, and the implementation effect is higher in high-polluting areas, thereby indicating that the market cannot take into account regional differences. Therefore, when formulating policies, it is necessary for the government to combine regional characteristics to achieve differentiated market governance.
(3) Establish perfect supervision. This study finds that the policy effect is higher in areas with strict environmental regulation, indicating that the effective implementation of environmental regulations requires strict supervision. Therefore, the government must strengthen project supervision to ensure the effective implementation of emissions trading policy. First, the amount of pollutant emissions of enterprises is the focus of this policy, and the government should increase the monitoring of pollutant emissions by enterprises to ensure the accuracy of pollution emissions monitoring. Second, the government can establish a corporate credit platform to expose companies that have violated regulations, and effectively supervise the behavior of companies through social forces such as the media and the public.

6. Conclusions

In this study, the difference in differences (DID) method is used to test the ETP's effectiveness. Firstly, a slack-based model with directional distance function (SBM-DDF) is used to measure industrial green innovation efficiency. Secondly, the DID model is used to evaluate the effectiveness of the policy effects and its impact on green innovation efficiency. Finally, a heterogeneity analysis is performed to analyze different policy scenarios in regions with different levels of pollution and different intensities of environmental regulation.

Further results from this research study indicate that:

(1) The industrial green innovation efficiency of each province in China is generally increasing year by year, and the development of the industry is gradually changing to incorporate both green and sustainable development;
(2) In the evaluation of the emission reduction effect, the interaction term coefficient is significantly negative, thereby indicating that the ETP significantly reduces industrial SO_2 emissions, therefore, the policy is effective;
(3) In evaluating the impact on industrial green innovation efficiency, the interaction term coefficient is significantly positive, which indicates that the ETP also significantly improves industrial green innovation efficiency;
(4) According to the heterogeneity analysis, it is also observed that the ETP significantly improves industrial green innovation efficiency in high pollution regions and strict environmental regulation regions.

Overall, this study identifies that ETP can promote pollution reduction and green innovation in developing countries, and is conducive to achieving sustainable economic development. This has enabled the aim of the policy to be clarified and suggestions to be provided for implementation enhancement of future policies on emissions trading policy in other countries.

A limitation of this study is that the data involved is regional. Further research is needed at the national or company levels in order to obtain more detailed results and formulate more targeted policy recommendations. Another limitation is that only industrial companies are involved. Further consideration should therefore be given to obtaining data from other industries and/or other types of organizations (such as service companies as well as government organizations) to determine the consistency of the results of this study.

Declaration of competing interest

The authors declare no conflict of interest.

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