**Investigating the Role of the Emissions Trading Policy to Reduce Emissions and Improve the Efficiency of Industrial Green Innovation**

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**Highlights:**

* A DID model was used to evaluate effectiveness of emissions trading policy.
* The study expands the application of the knowledge production function.
* Empirical results identify that the emissions trading policy achieves a emissions reduction effect.
* Findings show that emissions trading policy improves industrial green innovation efficiency.
1. **Investigating the Role of Emissions Trading Policy to**
2. **Reduce Emissions and Improve the Efficiency of Industrial**
3. **Green Innovation**

# Abstract:

1. Rapid economic development usually leads to serious environmental pollution
2. problems. In order to solve the problem of pollutant emission in sustainable industrial
3. development, it is urgent to examine the implementation effect of emissions trading
4. policy (ETP) and its impact on green industrial development. This research study
5. adopts China’s ETP as a case study and selects provincial panel data from 2004 to
6. 2018. We first use a non-radial, non-directed, slack-based measure-directional
7. distance function (SBM-DDF) to measure industrial green innovation efficiency.
8. Then we use a difference in differences (DID) model to empirically test the emissions
9. reduction effect of China’s policy and whether it promotes industrial green innovation.
10. Thereafter, results show that (1) the ETP reduces sulfur dioxide (SO2) emissions
11. indicating the effectiveness of the policy; (2) the policy significantly improves
12. industrial green innovation efficiency, meaning it promotes the sustainable
13. development of the economy; (3) heterogeneity analysis highlights that ETP produces
14. greater benefits for the most polluted regions of China which have more strict
15. environmental regulations. The research study examines the effect of emissions
16. trading policy implementation from a new perspective. The study also provides a
17. reference point for China to further refine its policy mechanisms and for other
18. countries to formulate suitable ETP.

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1. **Keywords**: Emissions Trading Policy; Emission Reduction; Industrial Green
2. Innovation Efficiency; Difference in Differences

# 1 Introduction

1. Over the past few decades, the global economy has been growing rapidly,
2. however this growth has also changed the ecological environment of the planet. In
3. particular, China is now facing serious environmental problems (Ning et al., 2020).
4. Therefore, industrial development must be transformed from the traditional high
5. consumption production model (with its corresponding high levels of pollution) to a
6. more sustainable development model (Zhu et al., 2019; Chen et al., 2020). In this
7. context, green innovation is crucial to facilitate high-performance sustainable
8. economic development (Beise & Rennings, 2005; Borghesi et al., 2015). Green
9. innovation encompasses sustainable innovation, ecological innovation, and
10. environmental innovation. It relates to innovation activities focused on supporting
11. environmental protection and sustainable development (Rennings, 2000). Furthermore,
12. green innovation efficiency (GIE) is a reflection of the input and output efficiency (Li
13. & Zeng, 2020). In order to control environmental pollution, emissions trading is
14. widely used in countries such as the United States, Canada, China and Japan (Calel &
15. Dechezleprêtre, 2016; L. Zhang et al., 2018; Zhou et al., 2019).
16. As a paradigm of market-based incentive regulation, emissions trading policy
17. (ETP) are of great significance for both environmental protection and sustainable
18. development (H. L. Tang et al., 2020). Indeed, US economist John Dales (1968) first
19. proposed the theory of emissions trading, which was subsequently adopted by the US
20. Environmental Protection Agency (EPA) to enable protection of the environment. In
21. this context, emissions trading generates economic incentives through market
22. mechanisms, which stimulate companies to adopt innovative technologies and
23. processes to reduce emissions and realize sustainable development (Jaraite & Maria,
24. 2012; Bel & Joseph, 2018; Zhou et al., 2019). However, due to the influence of a
25. variety of factors, the issue of whether implementation of environmental regulation
26. policies can promote economic growth while protecting the environment has become
27. an important matter to be addressed. Consequently, the impact of environmental
28. regulation on green innovation has become a major concern for various scholars (Jin

55 et al., 2019; Zhang et al., 2019).

1. However, at present, the existing emissions trading policy research lacks the
2. effect evaluation from the perspective of industrial green innovation efficiency. Also,
3. the effect evaluation that is currently available mainly focuses on the environmental
4. effect evaluation with there being less consideration of economic effect evaluation
5. (Jaraite & Maria, 2012; Calel & Dechezleprêtre, 2016; Zhang et al., 2019; Xuan et al.,
6. 2020). Whereas other studies examine the impact of the emissions trading system on
7. innovation patents and corporate performance (Calel & Dechezleprêtre, 2016; Marin
8. et al., 2017). In addition, there are three contradictory viewpoints on the effect
9. evaluation of the existing emissions trading policy, which are as follows: promotion
10. (L. Zhang et al., 2018; Zhu et al., 2020; Lv et al., 2020), inhibition (Feng et al., 2018;
11. K. Tang et al., 2020) and non-linearity (Wang & Shen, 2016; Li & Zeng, 2020).
12. Moreover, there has been no exploratory research into the effectiveness of ETP, and
13. no evaluation framework has been developed to determine the effectiveness of ETP
14. from the perspective of industrial green innovation efficiency.
15. Therefore, the objective of this research study is to test not only the emission
16. reduction effect of emissions trading policy but also the impact of this policy on the
17. industrial green innovation efficiency. In order to address the objective, this study
18. adopts China's emissions trading policy in 2007 and selects the inter-provincial panel
19. data from 2004 to 2018. The study also uses the difference in differences (DID)
20. model to empirically test the panel data. The study expands the application of the
21. knowledge production function (Griliches, 1979; Jaffe, 1989) and incorporates ETP
22. into an innovation input-output framework. As a consequence of the examination of
23. environmental and economic effects in this study, relevant research on emissions
24. trading theory is further enriched to verify that the emissions trading policy not only
25. has the effect of emission reduction but also promotes the industrial green innovation
26. efficiency and enriches the application of emission trading theory at the international
27. level.

# 2 Literature review

## 2.1 Emissions trading policy

1. Industrial development and the resulting economic growth invariably create
2. pollution problems (Munasinghe, 1999). In order to address the negative externality
3. of environmental pollution, many regions have adopted environmental regulation (ER)
4. (Zhao et al., 2014; Zhou et al., 2019). For example, Song, Yang, et al. (2020) test the
5. direct and the indirect impacts of environmental regulations on environmental
6. pollution. Song, Li, et al. (2020) found that the environmental policy of expanding
7. prevention and control areas can effectively improve air quality. Externality refers to
8. the external effect of an economic entity on another economic entity. Externalities can
9. be positive or negative. The Coase Theorem (Coase, 1960) provides one way of
10. solving negative externalities. According to this theorem, external economic problems
11. are caused by unclear definitions of property rights and hence negative environmental
12. externalities can be potentially eliminated through the effect of market transactions −
13. with zero transaction costs and a clear definition of property rights, the market’s
14. spontaneity will automatically adjust resources to become Pareto optimal and
15. optimally allocate resources.
16. A specific application of ER is air pollution control (Yang et al., 2016). ETP
17. have been mainly studied from three perspectives: initial allocation (Woerdman, 2000;
18. Ellerman & Buchner, 2007; Wråke et al., 2010; Betz et al., 2010), pricing (Coggins &
19. Swinton, 1996; Fischer, 2008), and implementation (Bleischwitz et al., 2007; Jaraite
20. & Maria, 2012; Shin, 2013; Marin et al., 2017). The present study focuses on the
21. latter.
22. Studies of the effects of ETP mainly focus on environmental and economic
23. aspects. Martin et al. (2015), for example, investigated the impact of the EU
24. Emissions Trading Scheme (EU ETS) from the perspectives of emission reduction,
25. innovation, competitiveness, and economic performance. The main goal of the EU
26. ETS is to reduce emissions, with a further long-term goal being to stimulate
27. innovation, and many studies have evaluated the emission reduction effect of the EU
28. ETS (Bleischwitz et al., 2007; Sandoff & Schaad, 2009; Anderson & Maria, 2011;
29. Jaraite & Maria, 2012; Zhang et al., 2019; Xuan et al., 2020; Ren et al., 2020). For
30. example, Yan et al. (2020) studied the impact of China's carbon emissions trading
31. policy on the environment and examined the collaborative governance effects of EST
32. on air pollution from three aspects, namely haze, industrial SO2 and industrial smog.
33. Other studies not only focus on the effects of the EU ETS on emission reduction,
34. but also on the performance of the overall economy. Calel and Dechezleprêtre (2016),
35. for instance, found that the EU ETS promotes an increase in low-carbon innovation
36. patent applications. Anger and Oberndorfer (2008) studied the impact of the ETS on
37. the performance of German companies and found that it had no obvious impact on
38. company incomes and employment. Whereas Marin et al. (2017) employed
39. propensity score matching (PSM) and DID to test the effect on the economic
40. performance of companies, finding that ETS can improve turnover, mark-up,
41. investment intensity, and labor productivity. Furthermore, Zhu et al. (2020) used the
42. DID method to examine the impact of carbon emissions trading policy on the green
43. development efficiency. Yang et al. (2020) found that China's carbon emissions
44. trading policy expands the scale of employment while reducing emissions, achieving
45. double dividends and the Porter effect. W. Zhang et al. (2020) studied the impact of
46. emissions trading policy on the trading market efficiency and found that this policy
47. promotes economic growth while reducing emissions. In other work, H. L. Tang et al.
48. (2020) conducted an analysis of the impact of China’s emissions trading system on
49. innovation and productivity and found that although the ETP promotes innovation, it
50. has no impact on productivity. Moreover, Shin (2013) concluded that China’s pilot
51. areas did not institutionalize SO2 emissions trading and that the overall policy was
52. unsuccessful.

## 2.2 Green innovation efficiency

1. As a consequence of increasingly severe environmental problems, green
2. innovation efficiency, which is regarded as the embodiment of innovation factors and
3. resource utilization efficiency (Du et al., 2019), has become a highly topical research
4. area. This is based on the need to take environmental factors into consideration −
5. reflecting the efficiency of green innovation input and output, and thereby effectively
6. measuring the green innovation process of industrial companies (Li & Zeng, 2020).
7. Current research in this area mainly focuses on the measurement of green
8. innovation efficiency (Cheng & Yin, 2016; Du et al., 2019; Li & Zeng, 2020) and the
9. influencing factors involved (De Vries & Withagen, 2005; Demirel & Kesidou, 2011;
10. Triguero et al., 2013; Borghesi et al., 2015).
11. In terms of the measurement method and data selection, Li and Zeng (2020) use
12. a super-slack-based model (SBM) to measure the green innovation efficiency of some
13. highly pollutant industries in China from 2011 to 2015. Du et al. (2019) examined
14. data from 2009 to 2016 and used a two-stage network DEA model to measure and
15. analyze the differences in green innovation efficiency of regional industrial
16. companies in 30 provinces. Cheng and Yin (2016) used the data envelopment analysis
17. (DEA) model and found that although green innovation efficiency is growing in 30
18. provinces during 2008-2013, the growth is at significantly different interregional rates.
19. J. Zhang et al. (2020) used the SBM-DDF model to calculate green innovation
20. efficiency for the city of Xi'an in China during 2003-2016. Whereas Zhu et al. (2020)
21. used the super-efficiency SBM model to measure the green development efficiency in
22. 30 provinces in China.
23. Meng et al. (2016) systematically reviewed the literature on regional energy and
24. carbon emission efficiency (EE&CE) research from the aspects of application
25. attribute, variable scheme, model aspect, and analyzed the differences in the
26. calculation results of six different DEA models. Moreover, Meng et al. (2019) studied
27. the ranking reversal phenomenon of China's regional energy efficiency under
28. different DEA models (namely Radial, M-Radial, SBMT, RAM and DDF model).
29. In terms of variable index selection, Li and Zeng (2020) adopted R&D personnel,
30. R&D input and industrial energy consumption as input indexes, and the output index
31. selected effective invention patents per hundred million yuan of income and industrial
32. solid pollution utilization rate. J. Zhang et al. (2020) used labor, capital and resource
33. inputs as input indexes, output is GDP, green output, and non-expected output is SO2
34. emissions. In other work, Feng et al. (2018) primarily included the inputs of labor,
35. capital and energy. The expected output is the number of patents and sales revenue of
36. new products, while the non-expected output is the discharge of industrial waste water,
37. waste gas and solid waste. To sum up, the existing research is mainly aimed at
38. investigating 30 provinces in China and the DEA model is has been widely used,
39. where the measurement indexes are mostly input, output and non-expected output.
40. For the studies on the influencing factors, Borghesi et al. (2015) investigated the
41. link between the EU ETS and environmental innovations. De Vries and Withagen
42. (2005) studied the influence of the stringency of European SO2 emissions,
43. environmental policy, and innovativeness from 1970 to 2000, finding that strict
44. environmental policy stimulates innovation. While Demirel and Kesidou (2011) used
45. data from UK industrial companies to investigate the effect of policy and company
46. factors on different types of eco-innovations. K. Tang et al. (2020) used both a DID
47. model and a difference-in-difference-in-differences (DDD) model to test the effect of
48. command-and-control regulation on green innovation efficiency. Whereas Huang et al.
49. (2016) studied the impact of regulators on green innovation performance.
50. Furthermore, many studies have investigated the impact of environmental regulation
51. on green innovation, which has also become a recent priority research area (Huang et

189 al., 2016; Chen et al., 2017; Wang et al., 2020).

## 2.3 Relationship between ETP and green innovation efficiency

1. There has been a large number of studies into the effect of environmental
2. regulation. Cecere and Corrocher (2016), for instance, found that strict environmental
3. regulations have a stronger influence on innovation. Other studies (Yabar et al., 2013;
4. Y. Zhang et al., 2018) found that ER can improve technological innovation. Indeed,
5. many also believe that ER can promote green innovation (De Vries & Withagen, 2005;
6. Zhao & Sun, 2016; Wang et al., 2020). At present, there are mainly three viewpoints
7. on this matter, which are inhibition, promotion and non-linearity.
8. The first view is that environmental regulations have an inhibitory effect.
9. According to neoclassical economics, environmental regulation can promote
10. environmental protection but also leads to additional costs for companies, which will
11. further lead to a reduction in international competitiveness and become detrimental to
12. economic growth (Cecere & Corrocher, 2016; Xie et al., 2017). For example, You et
13. al. (2019) found that, under the influence of fiscal decentralization and political
14. competition, environmental regulation cannot promote green innovation. Feng et al.
15. (2018) concluded that ER significantly inhibits green innovation efficiency in the
16. manufacturing industry. Further, K. Tang et al. (2020) found that command-control
17. regulation can inhibit companies’ green innovation efficiency. Whereas Blind (2012)
18. argued that ER has a negative effect on innovation performance, while Shi et al. (2018)
19. found that China’s Emissions Trading Pilot significantly inhibits industrial innovation.
20. The second is view is that there is a promoting effect. Although Porter and
21. Linde (1995) put forward an alternative view, in that legitimate and strict ER can
22. actually inspire companies to invest more in innovative activities to enhance
23. competitiveness, thus reducing the additional environmental costs of companies and
24. creating a win-win situation between the environment and the economy. Scholars
25. have found that market-based incentive regulation has a greater influence on emission
26. reduction and green innovation (Requate, 2005; van den Bergh et al., 2011). Zhao et
27. al. (2014), for instance, explored different types of environmental regulation (i.e.
28. command-control and market-based) − proposing that market-based incentive
29. regulation is more conducive to the transformation to a green development strategy.
30. Lv et al. (2020) identified that strict environmental regulation promotes corporate
31. innovation, whereas loose environmental regulation can reduce company innovation
32. and lead to an increase in the number of environmental related patents. L. Zhang et al.
33. (2018) found that ETP can promote companies’ green innovation. Whereas Zhu et al.
34. (2020) found that China's carbon emissions trading policy promotes green
35. development efficiency.
36. The third view is that some scholars believe that the relationship between ER and
37. green innovation is not only a simple linear relationship, but a nonlinear relationship.
38. Li and Zeng (2020) employed regression analysis and found a U-shaped relationship
39. between environmental regulation and green innovation efficiency. Whereas Wang
40. and Shen (2016) first calculated environmental productivity through the GML index
41. and studied the impact of environmental regulations on it. The study found an
42. inverted U-shaped relationship between the two. Shen et al. (2019) studied the
43. nonlinear effects of different types of environmental regulations on environmental
44. total factor productivity (ETFP), and identified that in light-polluting industries,
45. market-incentive environmental regulations have an N-type relationship with green
46. total factor productivity. Zheng et al. (2020) also found that there is a U-shaped
47. relationship between environmental regulation and economic efficiency.

## 2.4 Knowledge gap

1. The above review of the literature reveals two clear knowledge gaps, which are
2. summarized as follows.
3. *(1) There is a lack of research into industrial green innovation efficiency as a policy*
4. *effect.*
5. Despite environmental factors having become the focus of research into
6. traditional innovation efficiency, there is still limited research into green innovation
7. efficiency. Most research into the effects of environmental regulation are focused on
8. developed countries and fails to distinguish between different forms of environmental
9. regulations. Existing research focuses on the effects of emission reduction, including
10. the economic effects represented by patents, but rarely examines the effects of
11. environmental regulation. The use of specific environmental regulations to test the
12. effect of green innovation efficiency can produce more accurate assessments, which
13. 251
14. 252

are helpful for enriching environmental regulation policy theory.

1. *(2) There is a need for further verification of the effect of specific environmental*
2. *regulations.*
3. The conclusions from research into the impact of environmental regulation are
4. presently mixed, since promotion, inhibition and non-linear relationships have all
5. been identified. An important issue is to understand the impact of the ETP as a typical
6. policy of market-based incentive environmental regulation. Also, there is a need to
7. further study the extent to which emissions trading policy can achieve emissions
8. reduction and promote industrial green innovation under the dual pressure of
9. economic growth and environmental protection. Further research into ETP can help to
10. 262
11. 263

better evaluate the effects of these policies and test Porter’s Hypothesis(Mohr, 2002).

# 3 Methodology

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

270     (1)

1. where *innovi* denotes the innovation efficiency of provinces; *i* is a Chinese province;
2. A is the coefficient of input; *inputi* is the input of provincial innovation, mainly the
3. impact of innovation efficiency but including environmental regulation and specific
4. environmental policy; *β* is the output elasticity of the city’s innovative input. Factors
5. such as economic development level, foreign direct investment (FDI), education level,
6. industrial scale, and industrial structure are also included.

## 3.1 Difference in differences (DID)

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

290 al., 2019; Yang et al., 2020).

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

296       (2)

1. where *du*\**dt* is the time and policy interaction term, and its coefficient *β3* reflects the
2. effect of the policy. As shown in Table 1, substituting values into (1) and (2) enables
3. the result of the two differences, *β3*, to be obtained − the measure of the effect of the
4. policy.
5. 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 )

Non-pilot areas (Control group, *du*=0)

*β0*+*β1 β0*+*β1*+*β*2+*β3 β2*+*β3*

*β0 β0*+*β2 β2*

Difference *β1 β1*+*β3* ∆∆d=*β3*(DID)

1. 302
2. For example, DID is used here to evaluate the effectiveness of China’s ETP in
3. 2007. Therefore, the pilot provinces of the policy are deemed “treatment groups”, and
4. the provinces that have not adopted the ETP are considered “control groups”. In order
5. to solve the endogeneity problem caused by missing variables, control variables based
6. on (2) are included to give

308         (3)

1. where the subscripts *i* and *t* denote the province and year respectively, and the
2. independent variable Y is the natural logarithm of the industrial SO2 emissions and
3. industrial green innovation efficiency respectively. *D* is the policy dummy, being 1
4. for the provinces that adopt the ETP, and 0 otherwise. *T* is a time dummy, being 1 for
5. the time after policy adoption (2007), and 0 otherwise. *D*\**T* is the interaction of the
6. policy variable and time variable. The purpose of coefficient *β1* is to evaluate policy
7. effectiveness. An estimated result of *β1*>0 indicates that the ETP has a positive effect
8. on the dependent variable *Y*, otherwise it has a negative effect on *Y*. *ε* is the random
9. disturbance term of the model. *Z* is the control variable. λt is the time-fixed effect, and
10. μi is the regional fixed effect.

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

1. Data envelopment analysis (DEA) can be used to calculate the efficiency of
2. multiple inputs and multiple outputs (J. Zhang et al., 2020; W. Zhang et al., 2020;
3. Meng et al., 2016). The earliest CCR model was used to determine efficiency by
4. analyzing input and output data (Charnes et al., 1978). Thereafter Banker et al. (1984)
5. proposed the classic BCC model. Radial models, such as CCR and BCC, which are
6. widely used (Meng et al., 2019).
7. Initially, the environment and resources are taken as inputs (Reinhard et al.,
8. 1999). With the intensification of economic and resource conflicts, Chung et al. (1997)
9. proposed the directional distance function (DDF) model with environmental pollution
10. as an unexpected output. However, the traditional directional distance function has
11. radial and directivity of input and output, when there is excessive input or insufficient
12. output which leads to deviations from the true efficiency value.
13. In order to solve the problem of slack variables, Tone (2001) proposed a non-
14. radial, non-oriented Slacks Based Measure (SBM) model to solve the problem of
15. increasing or decreasing the proportion of input and output and it can be observed that
16. SBM and DDF models have gradually become popular with researchers (Meng et al.,
17. 2016). Therefore, Fukuyama and Weber (2009) combined SBM and DDF to obtain a
18. non-radial, non-directed Slack-based measure-directional distance function (SBM-
19. DDF), which not only avoids calculation distortion but also overestimates the
20. efficiency when the DDF model has slack variables. This approach also treats
21. environmental pollution as an undesired output. which can measure efficiency more
22. realistically. Consequently, the SBM-DDF methodology has been employed to
23. measure industrial green innovation efficiency (J. Zhang et al., 2020).
24. In this research study, each province and city in China is a decision-making unit
25. 344

(DMU). x is the N inputs of the decision-making unit, x=(x , …=x ) ∈R\* ; y is the M

1 N N

345

expected outputs, y=(y , …=y ) ∈R\* ; b is K unexpected outputs, b=(b , …=b ) ∈

1 M M 1 K

1. R\* ; (xt , yt , bt ) is the input-output data of the ith region in period t, (gx, gy, gb) is the

K i i i

1. direction vector, (sx , sy , sk ) is the slack vector of input and output. Hence, the model is

n m b

1. defined as

∑

1. 349

⃗ ⃗⃗

 ∑

 ∑

 (4)

1. 350

s.t  ∑

     ∑

  ∑

1. 351

 ≥0, ∑

  =1, ;  ;

1. In order to solve expression (4) with linear programming methods, we obtain the
2. efficiency index, measured as the inverse of green innovation efficiency − the larger
3. the value, the lower the green innovation efficiency. When the direction vector

1. , n and    , m, the green innovation efficiency (GIE)

1. is

357 ⃗ ⃗⃗⃗ ⃗⃗ ⃗ ⃗ ⃗⃗ (5)

358 s.t

1. Since the inefficiency value ⃗⃗⃗ remains between 0 and 1, the GIE value also
2. remains between 0 and 1. Therefore, the larger the value is, the larger will be green
3. innovation efficiency.

## 3.3 Variables and data

1. The effect of the ETP adoption in the year 2007 is evaluated from two
2. perspectives. The first is to test ETP effectiveness (i.e. its emissions reduction effect).
3. The second is through measuring the effect on industrial green innovation efficiency.
4. Since the ETP mostly targets industrial companies, industrial SO2 emissions is
5. adopted as the control variable.
6. The variables involved in this research include dependent variables, an
7. independent variable, and the specified control variables. The dependent variables are
8. industrial SO2 emissions and industrial green innovation efficiency. The independent
9. variable is the dummy time and policy interaction term. The control variables are
10. economic development level, foreign direct investment, education level, industrial
11. scale, and industrial structure. The selection and meaning of each variable is
12. explained below.
13. One of the dependent variables is green innovation efficiency. As mentioned
14. earlier, SBM-DDF is used to measure industrial green innovation efficiency and input
15. and output indicators are selected with reference to common practices. The data are
16. from designated industrial companiesi. The input indicators are divided into human
17. input and capital investment. Here human input (L) is represented by the full-time
18. equivalent of R&D personnel, and capital investment (K) is represented by
19. expenditure on R&D. The output indicators are divided into expected output and
20. unexpected output. Expected output is represented by the number of patent
21. applications (P) and the sales revenue of new products (G). The unexpected output is
22. industrial SO2 emissions.
23. The specific control variables are as follows:
24. (1) *Economic Development Level* – *Gross Domestic Product (GDP).* GDP affects
25. green innovation efficiency, and areas with high economic development are
26. expected to attach importance to innovation. Thus, the value is represented by the
27. natural logarithm of GDP per capita.
28. (2) *Foreign Direct Investment (FDI).* FDI provides improved innovative technologies
29. and resources, and the competitive effect also leads to companies paying more
30. attention to innovation. Therefore, FDI is represented by the ratio of the amount of
31. foreign investment to GDP.
32. (3) *Education Level (EDU).* New Economic Growth theory holds that human capital
33. is the main driving force behind economic growth. As a consequence of
34. improving the education level, it is easier to absorb new knowledge and
35. technology, which is conducive to industrial green innovation. Therefore, EDU is
36. represented by the proportion spent on education in national budget expenditure.
37. (4) *Industrial Scale (IS).* Green innovation efficiency can vary according to different
38. industrial scales. For example, large companies are more willing to invest more
39. resources into promoting industrial green innovation efficiency. Therefore, the
40. value is represented by the ratio of industrial gross output value to the number of
41. industrial companies.
42. (5) *Industrial Structure (IS).* The emission intensity of the secondary industry is
43. higher than other industries and therefore the proportion of different (secondary or
44. primary/tertiary) industries may have different effects. The proportion of the
45. output value of the secondary industry to GDP is used to represent the value.
46. 408
47. 409
48. 410

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

1. Table 2 Variables definition table.

Variables

name

Variables

symbol

Variables definition References Cheng and Yin (2016),

Input indicators

Human input L Full-time equivalent of

R&D personnel

Du et al. (2019), Zhu et

al. (2019), Li and Zeng (2020)

Cheng and Yin (2016),

Output indicators

Capital investment

Expected output

Unexpected output

Economic

K Expenditure on R&D

G Sales revenue of new products

P Number of patent applications

E Industrial SO2 emissions

Natural logarithm of GDP

Du et al. (2019), Zhu et al. (2019), Li and Zeng (2020)

Cheng and Yin (2016), Du et al. (2019), Wang and Shao (2019), Zhu et al. (2019)

Cheng and Yin (2016), Du et al. (2019), Zhu et al. (2019)

Cheng and Yin (2016), Du et al. (2019), Jin et al. (2019), Xie et al. (2017),

Zhu et al. (2019)

development level

GDP

per capita Wang and Shao (2019)

Control variables

Foreign direct investment

Education

FDI

Ratio of the amount of foreign investment to GDP

The proportion spend on

Wang and Shao (2019), Zhu et al. (2019)

level EDU

Industrial SIZE scale

education in national

budget expenditure Ratio of the gross output value to the number of industrial companies

Jin et al. (2019)

Xie et al. (2017)

Industrial IS The proportion of the Jin et al. (2019), Yang et

structure output value of the secondary industry to the

al. (2020)

 GDP

## 3.4 Data selection

1. As early as 1987, there was emissions trading taking place between companies in
2. Shanghai. In 2002, the former State Environmental Protection Administration of
3. China selected seven provinces (namely Shanxi, Shandong, Jiangsu, Shanghai, Henan,
4. Liuzhou, and Tianjin) and China Huaneng to conduct pilot scale projects for SO2
5. emissions trading. In 2007, 11 provinces (namely Tianjin, Jiangsu, Hubei, Zhejiang,
6. Inner Mongolia, Hunan, Chongqing, Shanxi, Shaanxi, Henan, and Hebei) also
7. adopted pilot scale emissions trading (Shin, 2013).
8. As the ETP adopted in 2007 was more comprehensive than the 2002 version of
9. the policy, the scale and scope of emissions trading have also been expanded and
10. trading activity has become more active. The 2007 ETP is therefore selected to
11. empirically evaluate ETP effectiveness. Due to data collection restrictions, panel data
12. is selected from a total of 30 provinces (see Table 3).
13. Table 3 Specific grouping situation.

Group Treatment group (policy implementation)

Jiangsu, Zhejiang, Tianjin,

Control group

(policy not implemented) Liaoning, Jilin, Heilongjiang, Anhui,

Jiangxi, Fujian, Shandong,

Provinces

Hubei, Hunan, Inner Mongolia, Shanxi, Chongqing, Shaanxi, Hebei, Henan

Guangdong, Guangxi, Sichuan, Yunnan, Beijing, Shanghai, Hainan, Qinghai, Guizhou, Xinjiang, Gansu, Ningxia

1. All the data are from the China Statistical Yearbook (2005-2019) (China, 2005-
2. 2019a) and China Statistical Yearbook on Science and Technology (2005-2019)
3. (China, 2005-2019b). The selected timeframe is 2004-2018. In order to eliminate
4. price fluctuations, the producer price indices for industrial products provided in the
5. China Statistical Yearbook are used to rebase the gross output value of industry to the
6. 2003 level (Zhou et al., 2019). Similarly, the per capita gross regional product indices
7. are used to adjust per capita gross regional product values. Based on the exchange rate
8. provided in the China Statistical Yearbook, USD values are converted into the CNY
9. equivalent.
10. Table 4 provides descriptive statistics of the variables, including their arithmetic
11. 436
12. 437

means and standard deviations (SD).

1. Table 4 Descriptive statistics of specific variables. Variables All the samples

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | Obs. | Mean | Std. dev. | Min | Max |
| GIE | 450 | 0.81141 | 0.12435 | 0.52646 | 1 |
| LN SO2 | 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 |
| 439 |  |  |  |  |  |  |

# 4 Results

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

## 4.1 Time trend graph of industrial green innovation efficiency

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

## 4.2 Regression analysis

1. *(1) ETP effectiveness*
2. A two-way fixed effects model, comprising the time effect and individual effect,
3. is used to conduct the empirical tests (Zhang et al., 2019). The prerequisite for
4. studying the relationship between the ETP and industrial green innovation efficiency
5. is the ETP’s effectiveness. Firstly, according to model (3), the natural logarithm of
6. industrial SO2 emissions (LN SO2) is selected as the dependent variable.
7. Table 5 Examination of the effectiveness of emissions trading policy.

VARIABLES (1) (2) (3) (4) (5) (6) LN SO2 LN SO2 LN SO2 LN SO2 LN SO2 LN SO2

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)

-0.7614 -0.7238 -2.1414\* -2.0571\*

FDI

(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 |

1. Note: Standard errors in parentheses; \*\*\*, \*\*, \* indicates statistical significance at 1%,
2. 5% and 10% level, respectively; Year indicates time fixed effect, and Province
3. indicates individual fixed effect.
4. 466
5. The emissions reduction effect is examined by gradually incorporating other
6. control variables into the model (namely GDP, FDI, EDU, SIZE, IS). Table 5
7. summarizes the results, showing that the significance of the coefficients and symbols
8. of the variables do not change with the addition of the control variables, thereby
9. indicating that the results are quite robust. With the gradual addition of control
10. variables (GDP, FDI, EDU, SIZE, IS), the coefficient of the interaction term becomes
11. significantly negative and is stable near -0.17.
12. *(2) The ETP’s impact on industrial green innovation efficiency*
13. Table 6 shows the results for the impact of the ETP on the industrial green
14. innovation efficiency model by gradually adding the control variables GDP, FDI,
15. EDU, SIZE, and IS. Again, the significance of the coefficients and symbol of the
16. variables do not change with the addition of the control variables, indicating that the
17. results are still robust. However, the interaction term is always significantly positive
18. and basically stable near 0.03.
19. Table 6 Effect of Emissions Trading Policy on Industrial Green Innovation Efficiency. VARIABLES (1) (2) (3) (4) (5) (6)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| GIE | GIE | GIE | GIE | GIE | 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) |
|  | 0.0110 | -0.0101 | -0.0193 | -0.0024 | -0.0276 |
|  | (0.0591) | (0.0585) | (0.0586) | (0.0556) | (0.0621) |
|  |  | 1.0591\*\*\* | 1.0477\*\*\* | 0.6384\*\* | 0.6093\*\* |
|  |  | (0.2887) | (0.2883) | (0.2794) | (0.2813) |
|  |  |  | -0.4848 | -0.4240 | -0.4393 |
|  |  |  | (0.3066) | (0.2905) | (0.2910) |
| SIZE |  |  |  | -0.0448\*\*\* | -0.0447\*\*\* |

GDP FDI EDU

fixed effect effect

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  |  |  | (0.0065) | (0.0065) |
| IS |  |  |  |  | 0.0629 |
| 0.7146\*\*\* | 0.6123 | 0.7744 | 0.9331\* | 0.8137 | (0.0688)1.0235\* |
| Constant (0.0119) | (0.5485) | (0.5420) | (0.5502) | (0.5214) | (0.5698) |
| Provinces YES | YES | YES | YES | YES | YES |
| Time fixed 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 30 | 30 | 30 | 30 | 30 | 30 |

provinces

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| 482 | Note: Standard errors in parentheses; \*\*\*, \*\*, \* indicates statistical significance at 1%, |  |  |  |
| 483 | 5% and 10% level, respectively; Year indicates time fixed effect, and Province |  |  |  |
| 484 | indicates individual fixed effect. |  |  |  |
| 485 |  |  |  |  |
| 486 | 4.3 Robustness checks |  |  |  |
| 487 | In order to ensure the robustness of the results, robustness checks have been |  |  |  |
| 488 | conducted according to the following three perspectives. |  |  |  |
| 489 | *(1) “Parallel paths” assumption* |  |  |  |
| 490 | The DID method can solve the endogeneity problem caused by the factors that |  |  |  |
| 491 | do not change with time, and eliminate the influence of unobserved confounding |  |  |  |
| 492 | factors. However, DID requires that the GIE of the two groups maintain basically |  |  |  |
| 493 | parallel paths before implementation of the policy, that is, the most essential condition |  |  |  |
| 494 | for using DID is the “parallel paths” assumption (Zhang et al., 2019). Before 2007, |  |  |  |
| 495 | the two groups in Figure 1 were basically parallel, and the parallel paths were initially |  |  |  |
| 496 | verified. On this basis, the research study introduces the parallel paths test of the |  |  |  |
| 497 | interaction items (D\*T1, D\*T2, D\*T3) of the time dummy variables in the years |  |  |  |
| 498 | before 2007 and the policy dummy variable. If the interaction term is not significant, |  |  |  |
| 499 | it indicates that the two groups are not significantly different before the policy |  |  |  |
| 500 | implementation. Model (1) and model (2) in Table 7 are without control variables and |  |  |  |

1. with control variables added, respectively. The results show that although the
2. interaction term D\*T3 is significant, the three interaction items are still not significant.
3. Therefore, it can be observed that the empirical result conforms to the “parallel paths”
4. assumption. That is, before the implementation of emissions trading policy there is
5. not a significantly difference in the level of green innovation efficiency between the
6. two groups.
7. *(2) Counterfactual test by changing the year of the treatment*
8. It can be observed that other policies or influencing factors may potentially
9. impact the results of this research study. Therefore, the counterfactual test was carried
10. out by changing the policy implementation time (Jiménez & Perdiguero, 2017; Yang
11. et al., 2020). It is assumed that the policy implementation year was 2006, and the
12. sample period selected was 2004-2008. In this regard, if the result of the interaction
13. term coefficient is not significantly positive, then it is assumed that the improvement
14. of industrial green innovation efficiency is due to the emissions trading policy
15. implemented in 2007. Otherwise, it may be caused by other policies or factors. The
16. results are shown in Table 7. Model (3) assumes that the policy implementation time
17. is 2006 and does not add control variables; model (4) adds control variables based on
18. model (3). The interaction term coefficient in Table 7 is not significant, indicating that
19. the empirical result of this research is robust. That is to say, the improvement of the
20. green innovation efficiency is caused by implementation of the emissions trading
21. policy, not by other factors.
22. *(3) Randomly select pilot provinces*
23. In order to test whether the policy effect is caused by some unobservable factors,
24. this research study adopts a random selection of pilot provinces for the robustness test
25. (Yang et al., 2020). If the test result is not significant, it means that the main results
26. are reliable; otherwise, it indicates that there is a deviation in the regression results of
27. the study. In this research, random sampling was used to select 11 provinces among
28. 30 provinces as the treatment group and the rest of the provinces as the control group.
29. Model (5) and model (6) in Table 7 are without control variables and with control
30. variables added, respectively. The analysis highlights that the interaction term
31. coefficient is not significant, indicating that the empirical result of this research is
32. robust.
33. Table 7 Robustness checks

variables fixed effect effect

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| (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) | -0.0100 | -0.0157 | 0.0052 | 0.0164 |
| D\*T |  | (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 NO | YES | NO | YES | NO | YES |
| Provinces YES | YES | YES | YES | YES | YES |
| Time fixed 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 30 | 30 | 30 | 30 | 30 | 30 |

provinces

|  |  |
| --- | --- |
| 534 | Note: Standard errors in parentheses; \*\*\*, \*\*, \* indicates statistical significance at 1%, |
| 535 | 5% and 10% level, respectively. |
| 536 |  |
| 537 | 4.4 Heterogeneity analysis |
| 538 | Due to the differences in economic development of different Chinese provinces, |
| 539 | there is more serious environmental pollution in the more industrialized regions. It is |

1. expected, therefore, that environmental regulation may have a more intensive effect in
2. heavily polluted regions. Accordingly, the provinces are further divided into high and
3. low pollution regions in relation to the median pollution emissions. Models (1) and (2)
4. in Table 8 contain the results for the high and low pollution regions respectively,
5. indicating that the ETP’s effect was indeed better in high pollution regions. This is
6. obviously because local governments in high pollution regions usually pay more
7. attention to environmental treatment and are expected to adopt stricter environmental
8. regulations. Additionally, high pollution regions are comparatively more developed
9. and have higher levels of technological development, as it is also easier to promote
10. R&D activities as well as green innovation efficiency.
11. The ETP’s influence will also be related to institutional factors. This because its
12. effective adoption requires strict environmental supervision and implementation (Ren
13. et al., 2020). The different environmental regulation intensities also lead to different
14. ETP effects, the value of which is represented by the proportion of investment in the
15. treatment of industrial pollution to GDP. The median of the data is used to divide the
16. provinces into strict and tolerant environmental regulation regions. Models (3) and (4)
17. in Table 8 show the results, which indicate that, as expected, the ETP in strict
18. environmental regulation regions significantly improves industrial green innovation
19. efficiency.
20. 559

Table 8 Heterogeneity analysis.

(1) (2)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| VARIABLES | GIE | GIE | regulation GIE | regulation 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\*\*\* |
| Control | (0.7173) YES | (0.9678) YES | (0.0548) YES | (0.0794) YES |

(3)

(4)

High pollution regions

Low pollution regions

Strict environmental

Tolerant environmental

effect effect

|  |  |  |  |
| --- | --- | --- | --- |
| Provinces fixed YESTime fixed YES | YESYES | YESYES | YESYES |
| Observations 225 | 225 | 225 | 225 |
| R-squared 0.6317 | 0.5771 | 0.5657 | 0.6173 |
| Number of 15 | 15 | 15 | 15 |

provinces

|  |  |  |
| --- | --- | --- |
| 560 | Note: Standard errors in parentheses; \*\*\*, \*\*, \* indicates statistical significance |  |
| 561 | at 1%, 5% and 10% level, respectively. |  |
| 562 |  |  |
| 563 | **5 Discussion and policy implications** |  |
| 564 | This research study has generated a number of policy implications. Firstly, this |  |
| 565 | research indicates that the ETP reduces industrial SO2 emissions. Hence, China’s |  |
| 566 | emissions trading policy is effective and achieves the desired emissions reduction |  |
| 567 | effect. This result is consistent with Zhang et al. (2019) and Zhou et al. (2019), where |  |
| 568 | both studies found the emissions reduction effect to be associated with the ETP. This |  |
| 569 | is because the emissions trading policy implements total quantity control, which limits |  |
| 570 | the emission of pollution to a certain extent so as to achieve corporate emission |  |
| 571 | reduction. However, Shin (2013) found that emission reductions have not been |  |
| 572 | achieved. This is because the emissions trading policy is still at the initial stage of |  |
| 573 | introduction, resulting in inactive secondary market transactions and low enthusiasm |  |
| 574 | for corporate participation. Therefore, ETP it cannot effectively play the role of policy. |  |
| 575 | Moreover, this study investigates industrial enterprises above a designated size, which |  |
| 576 | are the main targets of the implementation of the policy and the main goal of |  |
| 577 | emissions reduction. Consequently, it is easier to conclude that the implementation of |  |
| 578 | emissions trading policy can reduce pollution emissions. This study provides direction |  |
| 579 | for the government to deal with environmental pollution problems and help solve the |  |
| 580 | current serious environmental pollution. |  |

1. Secondly, this study adopts the new perspective of green innovation efficiency to
2. measure the economic effects of China's emissions trading policy, and enriches the
3. application research of emissions trading theory at the international level. Multiple
4. indicators are used to measure industrial green innovation efficiency more effectively.
5. The results indicate that the ETP can improve industrial green innovation efficiency,
6. which is similar to the findings of Zhu et al. (2020) and L. Zhang et al. (2018).
7. Companies with lower levels of pollution can obtain economic benefits by
8. selling spare emissions capacity, which allows them to promote green innovation
9. strategies. Conversely, companies with higher levels of pollution need to purchase
10. spare emission capacity to meet their production emission needs. Therefore, although
11. the emissions trading policy will increase the pollution cost of enterprises in the short
12. term, in the long term, the economic compensation brought by the sale of excess
13. emission rights will stimulate enterprises to improve pollution control technologies
14. and increase the green innovation efficiency thereby offsetting the environmental
15. costs of enterprises (Ren et al., 2020). Unlike the results of K. Tang et al. (2020), this
16. is because the market-based ETP provide companies with greater flexibility in
17. reducing emissions (H. L. Tang et al., 2020; Ren et al., 2020) and the ETP’s
18. environmental costs are lower than other forms of command-control environmental
19. regulation. The research highlights that policy is not only conducive to promoting the
20. transformation and upgrading of enterprises but also helps achieve high-quality
21. economic development. It also reveals intuitively how the emissions trading policy
22. plays a long-term role in China's pollution control and economic development, and
23. provides an important reference for the Chinese government to establish
24. environmental regulations that achieve a win-win situation for the environment and
25. the economy.
26. This research study further examines the heterogeneity in different polluted
27. regions and different environmental regulation intensities and finds that the
28. implementation of emissions trading policy is improved in areas with high pollution
29. and strict environmental regulations. This result is consistent with the findings of
30. Cecere and Corrocher (2016). On the one hand, the stronger the implementation of
31. environmental regulations and the higher the cost of violations of the law, the lower
32. the possibility of violations of the law, and the more effective the implementation of
33. policy, as well as the realization of a win-win situation for the economy and the
34. environment. On the other hand, this is because companies that operate under more
35. strict environmental regulations tend to invest more capital in pollution-control
36. 616
37. 617

technologies (De Vries & Withagen, 2005).

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

# 6 Conclusions

1. In this study, the difference in differences (DID) method is used to test the ETP’s
2. effectiveness. Firstly, a slack-based model with directional distance function (SBM-
3. DDF) is used to measure industrial green innovation efficiency. Secondly, the DID
4. model is used to evaluate the effectiveness of the policy effects and its impact on
5. green innovation efficiency. Finally, a heterogeneity analysis is performed to analyze
6. different policy scenarios in regions with different levels of pollution and different
7. intensities of environmental regulation.
8. Further results from this research study indicate that:
9. (1) The industrial green innovation efficiency of each province in China is
10. generally increasing year by year; the development of the industry is gradually
11. changing to incorporate both green and sustainable development.
12. (2) In the evaluation of the emission reduction effect, the interaction term
13. coefficient is significantly negative, thereby indicating that the ETP significantly
14. reduces industrial SO2 emissions. Therefore, the policy is effective.
15. (3) In evaluating the impact on industrial green innovation efficiency, the
16. interaction term coefficient is significantly positive, which indicates that the ETP
17. also significantly improves industrial green innovation efficiency.
18. (4) According to the heterogeneity analysis, it is also observed that the
19. ETP significantly improves industrial green innovation efficiency in high
20. pollution regions and strict environmental regulation regions.
21. Overall, this study identifies that ETP can promote pollution reduction and green
22. innovation in developing countries, and is conducive to achieving sustainable
23. economic development. This has enabled the aim of the policy to be clarified and
24. suggestions to be provided for implementation enhancement of future policies on
25. emissions trading policy in other countries.
26. A limitation of this study is that the data involved is regional. Further research is
27. needed at the national or company levels in order to obtain more detailed results and
28. formulate more targeted policy recommendations. Another limitation is that only
29. industrial companies are involved. Further consideration should therefore be given to
30. obtaining data from other industries and/or other types of organizations (such as
31. service companies as well as government organizations) to determine the consistency
32. of the results of this study.
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