Technological Forecasting & Social Change 155 (2020) 119989

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

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

Emissions trading and firm innovation: Evidence from a natural experiment in China

Shenggang Ren, Yucai Hu*, Jingjing Zheng, Yangjie Wang

School of Business at Central South University, China

ARTICLE INFO

Keywords:
Emissions trading
Technological innovation
Environmental regulation

ABSTRACT

This study investigates the causal impact of market-based environmental regulation on firm innovation by examining a large-scale market-based regulatory attempt in a developing country, namely, China's sulfur dioxide (SO_2) emissions trading program. Based on the panel data of China's publicly traded firms from 2004 to 2015, we adopt the difference-in-differences (DID) model to examine the innovation effects of the SO_2 emissions trading pilot policy. The results show that the program leads to a significant increase in patents and environmental patents among regulated firms. And the innovation effects of the policy perform better in areas with a high level of environmental enforcement. In further analysis, we find that the program decreases SO_2 emissions and promotes industrial growth in pilot areas. These evidences imply that the market-based emissions trading policy indeed promotes firm innovation and environmental innovation even in the context of a developing country, which is conductive to a win-win situation in both environmental protection and economic growth.

1. Introduction

Air pollution and climate change are among the most pressing current global environment challenges. To address these challenges, emissions trading schemes (ETSs) have assumed an ever more prominent role among various environmental policies over past decades, and many countries have begun implementing ETSs. The early programs include such as the American Acid Rain Program and the European Union (EU) carbon emissions trading system etc. Until recently, Australia, New Zealand and Canada have also launched the programs to regulate greenhouse gas emissions. Other significant economic areas (e.g., Brazil and Mexico) are in the process of initiating ETSs. With so many programs in the works, ETSs are environmental policies with the largest economic scope in the world today (Calel and Dechezleprêtre, 2016; Taylor, 2012).

In the most basic form of the ETS, policy makers set a cap on the quantity of permissible emissions and distribute allowances to emitters that collectively sum to the cap. Firms can freely trade the allowances on the market but must surrender the number of allowances that are equivalent to the amount of emissions at the end of each year (Rogge et al., 2011; Taylor, 2012). The primary goal of the ETS is to achieve a given reduction target at minimal cost; however, it is also critical for such policy providing incentives for technological innovation. Because technological innovation is not only an important driving force for addressing long-term environmental problems and achieving sustainable environment (Inoue et al., 2013) but also an important factor on firms' productivity growth and competitiveness (Aghion et al., 2016). Therefore, the focus of this study is to examine whether a market-based ETS can influence firm innovation, which is a key determinant of a win–win solution for both environmental quality and economic growth.

In theory, an emissions trading program can create two sets of countervailing incentives: on one hand, the program allows firms to meet pollution reduction obligations by purchasing allowances from other emitters, which may reduce their incentive to innovate in the presence of uncertainty during the innovation process (Rogge et al., 2011; Taylor, 2012). On the other hand, the Porter Hypothesis postulates that strict but flexible environmental regulations, such as the ETS, may provide incentives for technological change (Cohen and Tubb, 2018; Jaffe et al., 2002). The ETS may provide incentives for sellers of allowances to innovate to reduce emissions and enable them to sell more allowances. The conflicting incentives imply that the overall impact of the ETS on firm innovation remains unclear.

On the empirical evidence side, abundant literature has investigated the innovation effects of such policy. Some studies suggest that the emissions trading program is a major driving force of technological innovation (Borghesi et al., 2015; Calel and Dechezleprêtre, 2016; Martin et al., 2011), whereas, other studies do not support this view

* Corresponding author.
E-mail addresses: renshenggang1975@csu.edu.cn (S. Ren), 344978605@qq.com (Y. Hu).

https://doi.org/10.1016/j.techfore.2020.119989
Received 13 May 2019; Received in revised form 11 February 2020; Accepted 29 February 2020

(Gagelmann and Frondel, 2005; Taylor, 2012), and the results for the innovation effects of the policy tend to differ according to the design factors (Xu et al., 2019; Taylor, 2012). Moreover, these studies are mainly concentrated on the programs under the developed economics settings (e.g., Borghesi et al., 2015; Calel and Dechezlepretre, 2016; Hoffmann, 2007; Rogge et al., 2011; Taylor, 2012), resulting in a lack of studies based on the developing country settings.

We utilise China's SO_2 ETS pilot policy to investigate the innovation effects of the ETS, which has the following advantages. First, as the largest developing country, China's fast economic growth in recent decades has been accompanied by severe environmental degeneration, including overexploitation and mass industrial pollution, which are commonly observed in fast-growing economies (Cai et al., 2016). Our study, which is based on China's SO_2 ETS pilot policy, helps reveal the effectiveness of such policy in the developing world. Second, China's pilot policy provides a unique setting to evaluate the effects of the program. We explore the fact that the pilot policy covers the mining, manufacturing sectors in only 11 of the 31 provinces in mainland China. The pilot provinces, which are designated by the central government, are located in the eastern, central and western regions and vary extensively in both geographical distribution and economic circumstances (Jotzo and Löschel, 2014). Due to the top-down nature of the program design, the pilot policy can be considered a quasi-natural experiment. Therefore, the policy offers an opportunity to use the difference-in-differences (DID) model to examine the policy effects, which can avoid endogeneity issues caused by environmental regulations measured with errors (Cai et al., 2016; Chung, 2014).

This paper contributes to the literature in the following two dimensions. First, this study offers an empirical analysis of the causal effect of the ETS on firm innovation in a developing country context, which supplements a complete picture of the ETS innovation effects with different institutional backgrounds. Although some studies conducted under developed country settings have investigated whether the ETS can induce innovation (e.g., Rogge et al., 2011; Borghesi et al., 2015; Calel and Dechezlepretre, 2016; Hoffmann, 2007; Taylor, 2012), it is precisely in the developing countries facing serious environmental pollution that effective regulation is most needed. More importantly, such as those observed in these countries, to attract more FDI inflow as a source of economic development, relatively weak environmental policies may give developed countries a comparative advantage in pollution intensive goods, which is commonly known as the Pollution Haven Hypothesis (Sapkota and Bastola, 2017). However, relatively weak environmental regulations may be an important influencing factor in effectively implementing advanced market-based ETS in these countries (Hanna, 2010). With this, whether such market-based policy instrument can effectively implement and further address environmental challenges may be particularly significant for developing countries. Our findings suggest that the cap-and-trade can indeed incentivize firms to innovate even in a developing country context. The experience of China's pilot policy provides a reference and inspiration for the developing world to use the market-oriented ETS to address serious environmental challenges and the tradeoff between environmental quality and economic growth.

Second, our findings also contribute to the literature on environmental regulation and innovation. Around this issue, there has been a heated debate about the classical Porter Hypothesis (Porter, 1991; Porter and van der Linde, 1995), while it has only been substantiated by mixed evidence (Ambec et al., 2013; Chakraborty and Chatterjee, 2017; Jaffe and Palmer, 1997). This study provides new empirical evidence of market-based environmental regulation and firm innovation; the results suggest that the market-based emissions trading program can indeed incentivize firms to innovate, which supports the “weak” version of the Porter Hypothesis (Jaffe and Palmer, 1997; Porter and van der Linde, 1995).

The remainder of this paper is organized as follows. Section 2 summarizes the literature on the impact of environmental regulations on innovation and the SO_2 emissions trading policy in China. Section 3 reports the research design. Section 4 presents the empirical results analysis, and Section 5 presents further analysis. Section 6 concludes the paper.

2. Background and related literature

2.1. Environmental regulation and technological innovation

According to the Oslo Manual (OECD, 2005), innovation is the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practice (Kemp and Pearson, 2007). Technological innovation, which is the focus of this paper, is the use of new technology to produce changes in products or services, or the ways in which products or services are produced (Damanpour, 1987). Therefore, technological innovation can be considered the incorporation of technology into the development of new products or processes (Stock et al., 2002). And it is usually characterized as a process that encompasses three major stages: invention, innovation and diffusion (del Río González, 2009; Jaffe et al., 2002).

The drivers of technological innovation are generally classified as: 1) the supply-side push for R&D activities (Jaffe et al., 2002; Kesidou and Demirel, 2012); 2) the demand-side pull for innovation diffusion (Horbach, 2008; Marchi, 2012; Pavitt, 1984; Wagner, 2007); 3) the firm specific factors. Firm innovation capabilities, knowledge transfer mechanisms, and involvement in networks are particularly important for firm innovation (Ardito et al., 2016, 2019a; Horbach et al., 2012; Rogge et al., 2011); and 4) the impact of environmental regulations for limiting firms’ pollution activities on technological innovation, such as technical standards, Pigouvian taxes, subsidies, and tradable permits (Aghion et al., 2016; Fowlie, 2010; Frondel et al., 2008). With increasingly severe environmental pollution issues, the effect of environmental regulations on technological innovation has gradually become a key academic topic.

Focusing on the environmental regulation and technological innovation, Porter and van der Linde (1995) proposed the Porter Hypothesis, which stated that appropriate and strict environmental regulations can enhance corporate productivity and competitiveness through technological innovation. Many studies have examined whether more stringent environmental regulation promotes innovation. Some studies claim that traditional command-and-control regulations may force firms to reduce pollution emissions by, for example, developing new end-of-pipe technologies such as costly desulfurization equipment. However, once firms meet the emissions target, these regulations do not provide additional incentives for firms to conduct R&D activities to further reduce emissions (Lange and Bellas, 2005; Xie et al., 2017).

However, market-based environmental regulations (e.g., Pigouvian taxes (fees), subsidies, and tradable permits) are generally regarded effective regulations by providing firms the flexibility in choosing compliance strategies (Ambec et al., 2013; Brunnermeier and Cohen, 2003; Dechezleprêtre and Sato, 2017; Rogge et al., 2011). For example, environmental tax (fee) aims at internalizing the marginal social damage from pollution and thus reducing firm pollution negative externality (Bansal and Gangopadhyay, 2003). Jaffe and Palmer (1997) and Brunnermeier and Cohen (2003) found that pollution abatement expenditures lead to higher research and development expenditures and more environment-related patents. Similarly, environmental subsidy attempts to subsidize the economic return of firms’ environmental R&D activities due to market failure and avoid the double externality problem (Ardito et al., 2019b; Rennings, 2000). Johnstone et al. (2010) showed that public expenditures on R&D have a positive and significant effect on innovation with respect to wind and solar power. Guo et al. (2016) found that the government subsidy backed firms generate significantly higher technological and commercialized innovation outputs compared with their non-backed counterparts and the same firms before winning the grant.

Different from environmental taxes (fees) and subsidies, the emissions trading programs seem to take into account both the positive and negative externalities of corporate environmental activities. On the basis of limiting the firm's initial emissions allowances, firms are free to buy additional allowances or sell excess allowances at whatever price the market will bear, thus improving their compliance cost or allowance revenue. This is to say that, under the ETS, firms are always given flexibility to buy permits or invest in abatement technology based on their own actual situation. Given differences in policy design, it is likely that the policy effects will be different.

2.2. Emissions trading and technological innovation

The emissions trading program as a market-based environmental regulation has been increasingly used around the world to address environmental challenges. Over the past few decades, existing studies have examined many aspects of the program, including impacts on emissions abatement (e.g., Anderson and Maria, 2011; Bel and Joseph, 2015; Clò et al., 2017; Ellerman and Buchner, 2008), economic performance and competitiveness (e.g., Albrizio et al., 2017; Anger and Oberndorfer, 2008; Costantini and Mazzanti, 2012), and incentives for technological innovation (e.g., Martin et al., 2011; Popp, 2003; Rogge et al., 2011; Taylor, 2012).

Following the seminal contributions by Porter (1991) and Porter and van der Linde (1995), many studies have investigated whether the emissions trading policy will induce firms to promote innovation, and several studies have found evidence that the program does have an impact on technological innovation. For example, based on an investigation of the German electricity sector, Hoffmann (2007) showed that the EU ETS affects small scale investments with short amortization times, but not R&D efforts. Similarly, in a case study consisting of 42 electric power companies, Rogge and Hoffmann (2011) suggested that the EU ETS has a positive impact on the speed and direction of technological change. Martin et al. (2011) conducted interviews with nearly 800 European manufacturing firms and found a positive effect of the expected future stringency of EU ETS. These innovation effects are confirmed by newly empirical studies by Calel and Dechezlepretre (2016), who used a matched DID estimate of the treatment effect implies that the EU ETS is responsible for a 36.2% increase in low-carbon patenting among matched sample of 3428 EU ETS firms.

While there appears to be a general link between emissions trading and technological innovation, more careful reading of the literature yields a mixed conclusion which is particularly relevant to the institutional factors, such as the cap stringency, allowance price and predictability etc. (Xu et al., 2019; Taylor, 2012). Some studies argue that an overly generous allocation of emissions permits would largely undermine the incentives to innovate (Gagelmann et al., 2005; Grubb et al., 2005). However, Borghesi et al. (2015) suggested that the sectors under the program are more likely to innovate than non-ETS sectors but a sector's specific policy stringency is negatively associated with environmental innovations. Moreover, when lower-than expected allowance prices were observed, Taylor (2012) found that the program does not provide sustained incentives for private sector R&D investments in clean technologies. In addition, a few case studies and expert interviews indicate that firms tend to introduce well-known technological solutions rather than developing new technologies (Tomás et al., 2010).

Overall, few large scale empirical investigations of the innovation effects of the ETS have been conducted, and the results remain partially controversial. Moreover, existing research is primarily based on emissions trading in developed economies such as Europe and the United States. However, we are not aware of any study that examines the impact of emissions trading program on firm innovation in the developing country context. Therefore, our research on China's SO_2 ETS pilot policy should reveal the effectiveness in the developing world.

2.3. China's SO_2 emissions trading program

Since 1980, the growing concern that acid rain is damaging aquatic ecosystems, forests, buildings and public health in China has continually increased. To address this issue, the Chinese government started to implement a series of regulatory policies. Specifically, the State Council first issued *the Law on Prevention and Control of Atmospheric Pollution* in 1987; this law was consequently amended in 1995. In 1998, the State Council approved and implemented the two control zones (TCZ) policy, i.e. acid rain and SO_2 pollution control areas, and established corresponding reduction targets for pollution controls in the TCZ cities. These early policy instruments were successful in mitigating pollution emissions to a certain extent.

To encourage firms to reduce emissions through market mechanisms and based on the lessons learned from a failed SO_2 emissions trading program launched in early 2000, China started a pilot program in 11 provinces in 2007.[1] Approved by the Ministry of Finance and the Ministry of Ecology and Environment, the pilot areas include Jiangsu, Tianjin, Zhejiang, Hubei, Chongqing, Hunan, Inner Mongolia, Hebei, Shaanxi, Henan, and Shanxi provinces (Fig. 1 shows the 11 pilot provinces with the SO_2 emissions trading policy).

Similar to all other emissions trading initiatives, the program primarily includes the following aspects: 1) coverage. The major pollutants covered by policy include SO_2, COD, and ammonia nitrogen in the mining, manufacturing, and electricity sectors; 2) cap setting. Provincial level caps are determined by the central government according to its actual emissions in a base year,[2] and the total number of allowances issued is equal to the cap. The same approach is used to allocate the allowances across cities within each province and across firms within each city; 3) allowance trading. Allowances are traded through the ETS emissions exchange and the pilot provinces track allowance holdings, transfers, and cancellations by its electronic registry; 4) monitoring, reporting and verification (MRV). The pilot areas have developed a body of guidance, specification and methodology for MRV. In general, regulated firms are required to monitor, quantify annual emissions and report to a competent department before a given date and, 5) compliance. Firms are required to surrender allowances that are equal to their actual emissions at the beginning of each year. However, a firm will be penalized if it fails to surrender the allowances that are equivalent to its actual emissions; the most common approach is to impose a fine.

From the specific implementation of the policy, all pilot provinces have provided institutional foundations by establishing the provincial- or city-level emissions trading centres by 2012 and developing trading rules and guidelines as shown in Appendix Table A1. Local governments set a benchmark price for SO_2 emissions trading, however, the real transaction price exceeds the benchmark price in most provinces. The transaction volume in each province has rapidly increased in recent years. The accumulated transactions in Shaanxi and Chongqing reached 753 million yuan and 210 million yuan, respectively, by 2016.

[1] In 2002, China started to implement an SO_2 emissions trading program among 4 provinces, 3 cities, and 1 firm, but this original program failed to build an SO_2 emissions trading market. The program mainly focused on the electricity industry in some of the cities of a given province, rather than covering the whole province. Meanwhile, there were no centralized trading centres and there were only very the limited transactions between local governments.

[2] The previous year is usually used as the base year for the next Five-Year Plan period. For example, the year of 2010 is the base year of the 12th Five-Year plan period (2011-2015).

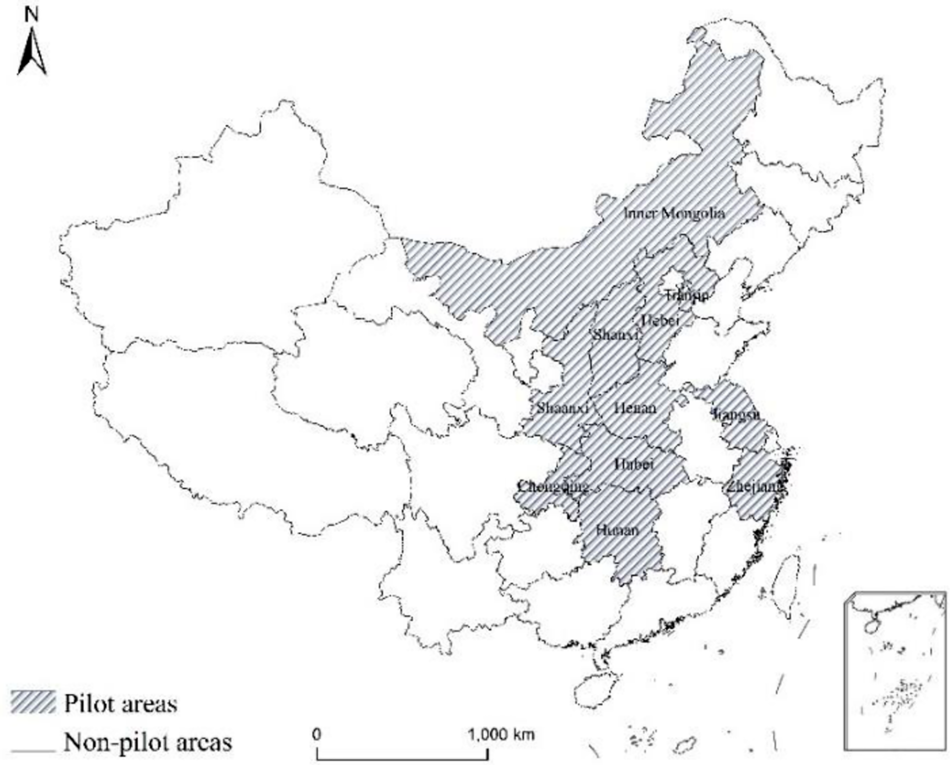

Fig. 1. The geographical distribution of China's pilot areas.

3. Research design

3.1. Sample and data

We focus on publicly traded firms listed on the Shanghai or Shenzhen stock exchanges in mainland China between 2004 and 2015. We take the following three steps to collect the data applied in this research.

First, we determine the industries that emit SO_2 according to China's Environmental Statistic Yearbook 2014. The industries with SO_2 emissions are concentrated in three sectors – mining, manufacturing, and electricity – which accounted for nearly all SO_2 emissions (99%) in China. Given that the electricity generation infrastructure is mostly state-owned and emissions permits are only traded within electricity firms, we only focused on the firms in the mining and manufacturing industries, which accounted for approximately 61% of the total SO_2 emissions.

Second, we selected all listed firms that had SO_2 emissions from the above two industries. We manually collected the SO_2 emissions information from the annual disclosures and corporate social responsibility (CSR) reports of the listed companies in the two industries. Specifically, we defined a company as "SO_2 emitting" if the company had disclosed any of the following information: 1) that it had disclosed any SO_2 emission information; 2) whether its SO_2 emissions were in compliance with permits; 3) whether it had used desulfurization equipment, and 4) whether it had used coal in production. The *Environmental Disclosure Rules* in China issued in 2008 have provided the mandatory legal requirement that any firm from the above three industries must disclose SO_2 emission information in its annual report. The sampling selection method, combined with the mandatory environmental information disclosure rules, aims to generate a comprehensive sample for analysis.[3] This process led to a total 264 listed firms being selected from 15 2-digit National Standard Industrial Classification (NSIC) industries that are SO_2 emitters. To guarantee the stability and validity of the sample, firms suffering continued losses and at risk of being delisted (denoted as ST and *ST companies) are removed from the sample consistent with practices in the literature.[4] This procedure led to a total of 228 firms with SO_2 emissions. Our DID framework is based on this sample (89 firms and 139 firms in the pilot and non-pilot provinces, respectively).

Third, based on the codes of the listed companies determined above, we collected the firm-level information from two firm-level data sources. Information on patents is obtained from the SIPO (State Intellectual Property Office Of The P.R.C). The website provides complete information on all patents granted in China since 1985, including the application and publication number of the patent, application and grant year, type of the patent, and owner of the patent. Firm-level data on financial information, sales of products, and other firm-specific

[3] For sample selection, on the one hand, one may still be concerned that some

(*footnote continued*)
firms that actually emit SO_2 in practice might not report SO_2 emission information. We argue that, even if this is the case, these underreporting firms are most likely to be firms with fewer emissions. As we mentioned earlier, the SO_2 emission allowances are generally allocated to firms above a designated size. Thus, the firms with fewer emissions would be not affected by the emissions trading policy, and underreporting by lower-level emitters should not pose a serious threat to our estimation of the impact of the SO_2 emissions trading policy; On the other hand, according to "the mandatory environmental information disclosure rules", if one firm emits SO_2, then it enters our sample. There won't be sample selection bias caused by selective disclosure of firms with good environmental performance.

[4] ST is a special classification for listed companies that have suffered losses for two consecutive fiscal years; *ST refers to the listed company that has suffered losses for three consecutive years. Both ST and *ST companies carry the risk of being delisted, and their stock prices vary greatly. To avoid the influence of abnormal financial data, ST and *ST companies were generally deleted as outliers, a technique that has been widely used in the literature using listed firms' information.

characteristics are obtained from the China Stock Market and Accounting Research (CSMAR) Database, where data is extracted from corporate annual reports.[5] Since the financial statements of the listed firms are scrutinized by accounting agencies and leave less room for data fabrication, the quality of the firm-level data should be high (Boeing, 2016).

3.2. Measurement of key variables

3.2.1. Emissions trading program

Emissions Trading Program (*Treat*). This variable is a dummy variable that equals 1 if a firm's registered address is in the pilot provinces of the SO_2 emissions trading policy and equals 0 otherwise. There are a total of 11 pilot provinces: Jiangsu, Zhejiang, Tianjing, Hubei, Hunan, Henan, Shanxi, Chongqing, Shaanxi, Hebei, and Inner Mongolia. The remaining 20 provinces are regarded as non-pilot areas.

3.2.2. Outcome variables

Technological innovation (*Patent*). Patents have been used as the standard measure of innovation in the literature (Brunnermeier and Cohen, 2003; Guan and Yam, 2015). Although most patents do not create new products and new processes, the number of patents can serve as a valuable indicator of economically valuable knowledge and inventive activities. Compared with other proxies for innovation such as the number of new products or processes introduced by firms, they are less prone to subjective measurement errors. Hagedoorn and Cloodt (2003) suggest that patents are a reasonable indicator of innovative performance at the firm level.

We measure firm-level technological innovation by the number of new patent applications by a firm in each year.[6-7] In robustness checks, we employ the number of new invention patent (*I_Patent*) applications by a firm in a year as an alternative measure and obtain qualitatively the same results.

Environmental innovation (*E_Patent*). We further distinguish technological innovation into environmental innovation to explore firms' responses to pressure from environmental regulations (Antonioli et al., 2013). Similar to the environmental innovation definition of Brunnermeier et al. (2003) and Petruzzelli et al. (2011), environmental innovation is measured with the number of environmental patent applications. We determine an environmental patent by a keyword search in patent abstracts based on the method of Li et al. (2016). Specifically, we selected patents related to "desulfurization", "low carbon", "environmentally friendly", "green", "emission reduction", "energy conservation", "clean", "recycling", "economical", "sustainable", "ecological", and "environmental protection" as environmental patents.

3.2.3. Control variables

Firm size (*Size*). Large and capital-intensive firms generate more patents (Hall and Ziedonis, 2001). We apply the logarithm of total assets to control for firm size (Chang et al., 2015).

Firm age (*Age*). Firm age would alter the organizational context and hinder innovation due to the existence of organizational inertia (Guan and Yam, 2015). We use the number of years since a firm was founded as a measure of firm age.

Ownership structure (*SOE*). This variable denotes the firm ownership structure, which is a dummy variable that is equal to 1 if a firm is a state-owned enterprise; otherwise it equals 0.

Firm performance (*ROA*). The ratio of net income to total assets is controled to consider the impact of organizational performance on firm innovation (Cho and Kim, 2017).

Leverage (*Leverage*). The ratio of corporate liabilities to assets (liabilities/assets) is added to the model to consider the impact of current capital structure on innovation (Bronzini and Piselli, 2016; Chang et al., 2015).

Research and development expenditure (*R&D*). The inputs of innovation are often measured by research and development expenditure. We control for *R&D* in the regression model, which is measured by the ratio of the R&D expenses to total the assets in each year.

Export learning (*Export*). Firms can obtain advanced technology and management experience through export (Yang et al., 2017). We use a dummy variable as an indicator for export behavior, i.e., *Export* is equal to 1 if a firm has export business; otherwise it is equal to 0.

Industry concentration (*HHI*). Following Chemmanur and Tian (2018), we utilize the Herfindahl-Hirschman index to measure the industry concentration, which is constructed at the two-digit SIC level and select revenue as the scale for calculation.

Economic development (*Per GDP*). Following Fredriksson et al. (2004), we use the provincial per capita GDP to proxy regional economic development which is measured by the logarithm of the provincial GDP at the end of each year divided by the population.

Environmental Enforcement (*Enforce*). The latest research shows that the strict supervision and enforcement of laws is the primary driving force for improving environmental quality (Greenstone and Hanna, 2014). We use the number of environmental administrative punishment cases in each province to measure the local environmental enforcement.

Market Share (*Share*). Market share is one of the main drivers of a firm applying for patents. We employ the ratio of firm sales to national industry sales in each year to measure the firm's market share. The definitions of the variables in this paper are reported in Appendix Table A2.

3.3. Empirical model

Our empirical strategy compares changes in firm technological innovation between 2004 and 2015 in the treatment and control groups. The DID regression model we estimate for firm technological innovation (Y_{it}) is:

$$Y_{it} = \beta_0 + \beta_1 Treat_i \times Time_t + \beta_2 X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (1)$$

where i indexes firms, and t indexes years. $Treat_i$ is equal to 1 if a firm is located in one of the 11 provinces covered by the program; otherwise it equals 0. $Time_t$ equals 1 for every year after 2007; otherwise it equals 0. The coefficient β_1 on the interaction term is the standard DID estimator. If β_1 is significantly positive, we can infer that the SO_2 ETS is effective for increasing innovation. X_{it} includes a set of control variables. The variables γ_i and μ_t indicate firm fixed effects and year fixed effects, respectively. ε_{it} is the idiosyncratic error term.

The key assumption in using the DID model is the parallel trend assumption.To further test this assumption, we estimate the annual treatment effects of the policy, which could not only test the difference in the time trends between the two groups before the policy but also

[5] CSMAR is maintained by the China Accounting and Finance Research Centre of the Hong Kong Polytechnic University and Shenzhen GTI Financial Information Limited.

[6] According to the "Patent Law of the People's Republic of China", patents are divided into three categories: invention patents, utility model patents and design patents. The invention patents refer to new technical solutions proposed for products, methods or improvements; The utility model patent refers to a new technical solution that is suitable for practical use in terms of the shape, configuration, or combination thereof; The design patent refers to a new design that is aesthetically pleasing and suitable for industrial applications based on the shape, pattern, or combination of the products, and the combination of color and shape, and pattern. The "patent" in this study refers to the total number of three types of patents applied by a firm in each year; the "invention patent" refer to the number of invention patents applied by a firm in each year. Invention patents are often considered the most innovative.

[7] In fact, some listed companies may have several subsidiaries, and these subsidiaries may be located in different provinces. To avoid confusion of policy effects, we only focused the listed company itself. Therefore, the patent data of the subsidiary is not included in the patent measurement.

estimate the policy dynamic treatment effects. Specifically, we estimate the following equation:

$$Y_{it} = \beta_0 + \sum_{j=-3}^{8} \beta_t Treat_i \times Yeardum_{2007+j} + \beta_2 X_{it} + \gamma_i + \mu_t + \varepsilon_{it}, \tag{2}$$

where $Yeardum_{2007+j}$ is the indicator variable for year $2007+j$, and the default (omitted) year category is 2007. Thus, β_t captures the year effects from 2004 to 2015. Other variables are defined in Eq. (1).

Additionally, to rule out other concurrent environmental policies or other time-varying unobservables confounding factors, we choose another control group and conduct a triple-differences estimation in the robust tests. The control group includes all non-SO_2 emission firms from mining and manufacturing industries (excluding the firms identified in our baseline regression).[8] We compare changes in firm innovation among SO_2 emission firms with those among other non–SO_2 emission firms across the treatment and control groups before and after the policy:

$$\begin{aligned} Y_{ict} = {} & \beta_0 + \beta_1 Treat_i \times Time_t \times SO_2group_c + \beta_2 Treat_i \times Time_t \\ & + \beta_3 Time_t \times SO_2group_c + \beta_4 Treat_i \times SO_2group_c + \beta_5 X_{ict} + \gamma_i + \mu_t \\ & + \varepsilon_{ict}, \end{aligned} \tag{3}$$

where c indexes SO_2 emission status. SO_2group_c is equal to 1 if a firm produces SO_2 emissions; otherwise it equals 0. The triple-differences estimator β_1 measures the effect of the emissions trading policy on SO_2 emitting firms relative to that on non-SO_2 emitting firms. The estimator consistently estimates the effect of ETS on SO_2 emission firms if unobservables, such as other regulations, had the same effect on SO_2 emission and non-SO_2 emission firms. Other variables are defined in Eq. (1).

4. Empirical results

4.1. Baseline model estimations on technological innovation

Table 1 reports the summary statistics of the variables used in our analysis. The mean, standard deviation, min, median, and max values are reported in panel A. Panel B compares the changes in the pilot firms before and after the implementation of the policy with the corresponding changes in non-pilot firms during the same period. In column 3, compared with the pre-pilot firms, the average number of new patent applications of non-pilot firms after the pilot policy is 4.9, whereas that of the pilot firms is 15.2 (shown in column 6). Therefore, we could find that the pilot firms have more patent applications after the policy implementation. Meanwhile, before implementation of the pilot policy, pilot firms apply for 0.49 more patents than non-pilot firms (shown in column 7), whereas, pilot firms apply for 10.7 more patents than non-pilot firms after the policy implementation (shown in column 8). In addition, we also find the similar changes in *I_Patent* and *E_Patent,* which are our measurements of enterprise technological innovation.

Table 2 reports the DID estimates of the effects of the emissions trading policy on firm innovation based on three different measures of innovation. All three regressions consistently show a statistically significant positive correlation between emissions trading and firm innovation. Column 1 suggests that the emissions trading program is associated with 9.2 (or 28.3%) more patent applications per year. Columns 2 and 3 indicate that the treatment effects for invention patents and environmental patents are 3.5 and 1.0 (or 26.4% and 22.3%), respectively, which indicates that the policy promotes technological and environmental innovation among regulated firms.

Compared with existing studies, our findings are similar to those of the studies such as Borghesi et al. (2015) and Calel and Dechezleprêtre (2016) etc. Borghesi et al. (2015) found that the sectors under the program are more likely to innovate than non-ETS sectors. Calel and Dechezleprêtre (2016) investigated the effects of the EU ETS on technological change and found that the EU ETS increased low-carbon innovation among regulated firms by as much as 10%. Based on these empirical evidences, the ETS can indeed provide firms incentives to invest in new technologies. The potential reason for the conclusion is that the market-based ETS provides firms flexibility in choosing compliance strategies, while using the explicit price signal to incentivize firms' emissions reduction behavior is generally considered to be more effective (Yang et al., 2017). More importantly, the ETS remunerates any abatement effort due to technological improvements, either in the form of lower costs resulting from the reduced number of required allowances – or additional revenues – acquired through the sale of superfluous emission allowances (Gagelmann and Frondel, 2005).

4.2. Measuring the dynamic treatment effect

The key identification assumption behind the causal interpretation of the DID estimates is that the non-pilot firms provide valid counterfactual changes in technological innovation for the pilot firms, had they not been treated, conditional on covariates. A potential challenge to this assumption is that differential changes between the treatment and control groups may be driven by preexisting differences in the time trends. To address this issue, we estimate the annual treatment effects of the policy through Eq. (2).

The estimated annual treatment effects are plotted in Fig. 2. In the pre-pilot period (i.e., before 2007), the coefficients of *Patent, I_Patent* and *E_Patent* are statistic insignificantly, which implies that there are no systematic differences in pre-pilot time trends across the treatment and control groups, and thus, the parallel trend assumption is not violated. In the post-pilot period (i.e., after 2007), a clear upward trend of the yearly innovation effects is observed. The coefficients of *Patent, I_Patent* and *E_Patent* become statistically significant approximately three years after the policy was implemented. A potential reason for the lagging effects may be that the SO_2 emissions trading program encourages firm innovation through, for example, learning-by-doing, and the impact of the policy may take some time to materialize in terms of the patent applications and other measures.

4.3. Robust tests

4.3.1. Triple differences test

A potential threat to our findings is that the effect of SO_2 ETS may be driven by other concurrent environmental policy changes. For example, China started to implement the carbon emissions trading pilot policy in 2011, which covered 7 provinces and cities.[9] If this concurrent policy affects firms differently between pilot and non-pilot areas, our DID analysis would not provide the causal impact of the SO_2 ETS. Similarly, other time-varying unobservables may confound our results. For example, the changes in regional agglomeration may have affected firm innovation due to the movement of skilled workers and firms. To the extent these changes differ across the treatment and control groups, the DID estimates may be inconsistent.

To address these concerns, we conduct a triple-differences estimation by Eq. (3) as an additional test. Table 3 presents triple difference estimates. The results show that SO_2 ETS has a positive impact on

[8] There are a total of 291 firms without SO_2 emissions from the other two-digit industries. After ST and *ST companies were excluded, we finally come to a total of 185 non-SO_2 emitting firms as the control group.

[9] On October 29, 2011, the National Development and Reform Commission issued a "Notice on Carrying out the Pilot Project on Carbon Emissions Trading", and agreed to carry out carbon emissions trading market pilots in Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong and Shenzhen. Three of these 7 pilot provinces (Tianjin, Chongqing and Hubei) are also covered by the SO_2 emissions trading program.

Table 1
Descriptive statistics.

Panel A: Basic statistics

Variables	Mean	S.D.	Min	P50	Max
Patent	8.44	26.75	0	0	436
I_Patent	3.44	11.45	0	0	195
E_Patent	1.19	3.52	0	0	44
Size	22.10	1.33	14.16	22.04	25.91
Age	15.33	6.64	4	15	73
SOE	0.58	0.49	0	1	1
ROA	0.74	0.48	0.07	0.61	2.64
Leverage	0.55	0.22	0.10	0.56	1.51
R&D	0.46	1.01	0	0	11.63
Export	0.54	0.50	0	1	1
HHI	0.20	0.18	0.05	0.14	1
Per_GDP	10.28	0.65	8.35	10.36	11.59
Enforce	7.70	1.35	0	7.64	10.56
Share	0.67	1.85	0	0.21	30.14

Panel B: Characteristic of pilot and non-pilot firms before and after the policy

Variables	Non-pilot firms (1668)			Pilot firms (1068)			Difference	
	Pre-pilot Mean (1)	Post-pilot Mean (2)	Difference (3) = (2)-(1)	Pre-pilot Mean (4)	Post-pilot Mean (5)	Difference (6) = (5)-(4)	Pre-pilot (7) = (4)-(1)	Post-pilot (8) = (5)-(2)
Patent	2.26	7.22	4.96***	2.75	18.01	15.26***	0.49	10.79***
I_Patent	1.02	3.3	2.28***	0.59	6.98	6.39***	−0.43**	3.68***
E_Patent	0.41	1.13	0.72***	0.36	2.31	1.95***	−0.05	1.18***
Size	21.51	22.31	0.8***	21.58	22.48	0.9***	0.07	0.17**
Age	11.41	17.41	6***	11.21	17.21	6***	−0.2	−0.2
SOE	0.6	0.6	0	0.56	0.56	0	−0.04	−0.04
ROA	0.71	0.73	0.02	0.77	0.75	0.02	0.06*	0.02
Leverage	0.53	0.54	0.01	0.54	0.58	0.04***	0.01	0.04***
R&D	0.04	0.65	0.61***	0.08	0.68	0.6***	0.04**	0.03
Export	0.46	0.46	0	0.66	0.66	0	0.2***	0.2***
HHI	0.20	0.23	0.02**	0.15	0.18	0.02***	−0.05***	−0.05***
Per_GDP	9.75	10.55	0.8***	9.69	10.57	0.88***	−0.06	0.02
Enforce	7.44	7.55	0.11	8.09	7.94	−0.15***	0.65***	0.39***
Share	0.86	0.81	−0.05	0.47	0.41	−0.06	−0.39***	−0.4***

innovation among SO_2 emission firms relative to non-SO_2 emission firms, and the impact is significant at the 1% significance level. In the treatment group, SO_2 emission firms produce 20.6 more patents on average per year after the emissions trading policy compared with non-SO_2 emission firms.

4.3.2. Instrumental variable estimation

To further address the concern of endogeneity, for example, due to omitted variables that can be correlated with treatment status, we adopt an instrumental variable (IV) strategy as an additional robustness check (Cai et al., 2016). We use the average distance between a firm and the nearest coal mine as the instrument for the treatment status. The average distance is the same for all firms in a province and does not vary over time. Intuitively, the IV can be considered as a measure of access to coal for a given province. Firms in energy-intensive industries are more likely to choose to locate close to energy sources such as coal, ceteris paribus. As a result, these industries tend to be clustered in coal producing areas, and these areas are more likely to be selected as part of the emissions trading pilot area.

We first construct the distance between a firm's city and the city where the nearest coal mine was located. We then generate the average distance for all firms in a province. Table 4 report the first and second stages of the IV regressions. The first-stage results show that the IV is highly relevant for the treatment variable. The second-stage estimates show positive and statistically significant effects of the program on firm innovation, with the estimated impacts being similar to those from the DID regressions.

4.3.3. Other robustness checks

We conduct two other robust tests. First, the emissions trading imposes a regulatory burden on the firms covered by the program. Some firms, especially highly polluting firms, may change their domicile from a province in the pilot area to a province in the non-pilot area to avoid the compliance cost, leading to sampling selection bias. To address this concern, we eliminated the firms that enter or move out of the pilot area according to the registered address during our study period and re-estimated Eq. (1). Second, following the method of Brunnermeier and Cohen (2003), we estimate a Poisson count data model since our dependent variable – the number of patent applications Y_{it} – is a non-negative integer.

The results are reported in Table 5. The results of ruling out firm avoidance behavior with a reduced sample is presented in columns 1–3, and columns 4–6 report the estimated results of the Poisson model. The estimated impacts of the SO_2 emissions trading policy on innovation remains statistically significant.

4.4. Heterogeneity analysis

The practical policy effects of the ETS seem particularly relevant to the institutional factors, such as policy design approaches, policy enforcement and interactions with existing environmental policies (Taylor, 2012) etc., among which environment policy enforcement is closely relevant to developing countries, as the effective implementation of emissions trading system requires strict environmental supervision and enforcement (Chang and Wang, 2010). However, as we previously emphasized, many developing countries are experiencing serious environmental challenges, whereas, relatively weak environmental regulations may affect the effectiveness of market-oriented emissions trading policies in these countries. Therefore, the analysis of contextual factors such as environmental enforcement based on China's

Table 2
DID estimates.

Variables	Patent (1)	I_Patent (2)	E_Patent (3)
Treat × Time	9.174***	3.486**	1.022**
	(3.458)	(1.470)	(0.455)
Size	3.018***	1.507***	0.412***
	(1.131)	(0.517)	(0.154)
Age	−0.062	−0.237	−0.100
	(0.997)	(0.474)	(0.116)
SOE	−28.312*	−12.873*	−4.976**
	(16.283)	(6.625)	(2.341)
ROA	−6.871	−3.245	−0.829
	(4.675)	(2.332)	(0.589)
Leverage	7.118**	4.308***	0.516
	(2.932)	(1.384)	(0.391)
R&D	2.538**	1.056***	0.211
	(1.211)	(0.397)	(0.167)
Export	−1.076	−1.166	−0.741
	(6.180)	(1.942)	(0.900)
HHI	44.811	8.383	6.790
	(37.219)	(9.703)	(5.324)
Per GDP	3.957	3.525	1.171
	(8.204)	(3.872)	(0.926)
Enforce	0.027	0.208	−0.066
	(0.751)	(0.402)	(0.103)
Share	0.996	0.218	0.027
	(0.894)	(0.175)	(0.044)
Firm fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Constant	−96.078	−58.234*	−16.400**
	(65.672)	(32.375)	(7.742)
Observations	2736	2736	2736
R-squared	0.524	0.491	0.471

Note: Standard errors in parentheses are clustered at the firm level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

SO_2 ETS pilot policy helps us to better understand the policy effects.

To test the heterogeneous effects, we investigate whether firms under a higher level of environmental enforcement behave differently from other firms. Specifically, following Huang and Chen (2015) and Li and Ramanathan (2018), we apply the provincial environmental administrative penalty cases to proxy environmental enforcement (*Enforce*) and then divide our sample into two subsamples based on the median number of *Enforce*. The subsample above the 50th percentile of *Enforce* represents stricter environmental enforcement. The data is derived from the *China Environmental Statistics Yearbook*.

The regression results for the two subsamples are presented in Table 6. Columns 1–3 report the estimation results for the subsample with a higher level of environmental enforcement; and the remainder is the lower level. We find that the innovation effects remain robust in a stricter environmental enforcement subsamples. However, the coefficients of emissions trading become statistically insignificant for the lower level of environmental enforcement subsamples. This evidence suggests that the SO_2 ETS performs better in areas with high levels of environmental enforcement.

5. Further analysis

Our results show that the market-based ETS can incentivize firms to innovate. However, the classical Porter Hypothesis claimed that properly designed environmental regulations can lead to “innovation offsets” that will not only improve environmental performance but also partially – and sometimes more than fully – offset the additional cost of regulation. The argument is that well-designed environmental regulations may yield a “win-win” situation in some cases by not only protecting the environment but also enhancing profits via the improvement of products or their production processes (Ambec et al., 2013; Porter and van der Linde, 1995; Xie et al., 2017). Based on this point of view, we focus on whether the emissions trading pilot policy is a fruitful way to reconcile environmental and economic performance and achieve potential double economic-environmental dividends. Specifically, we

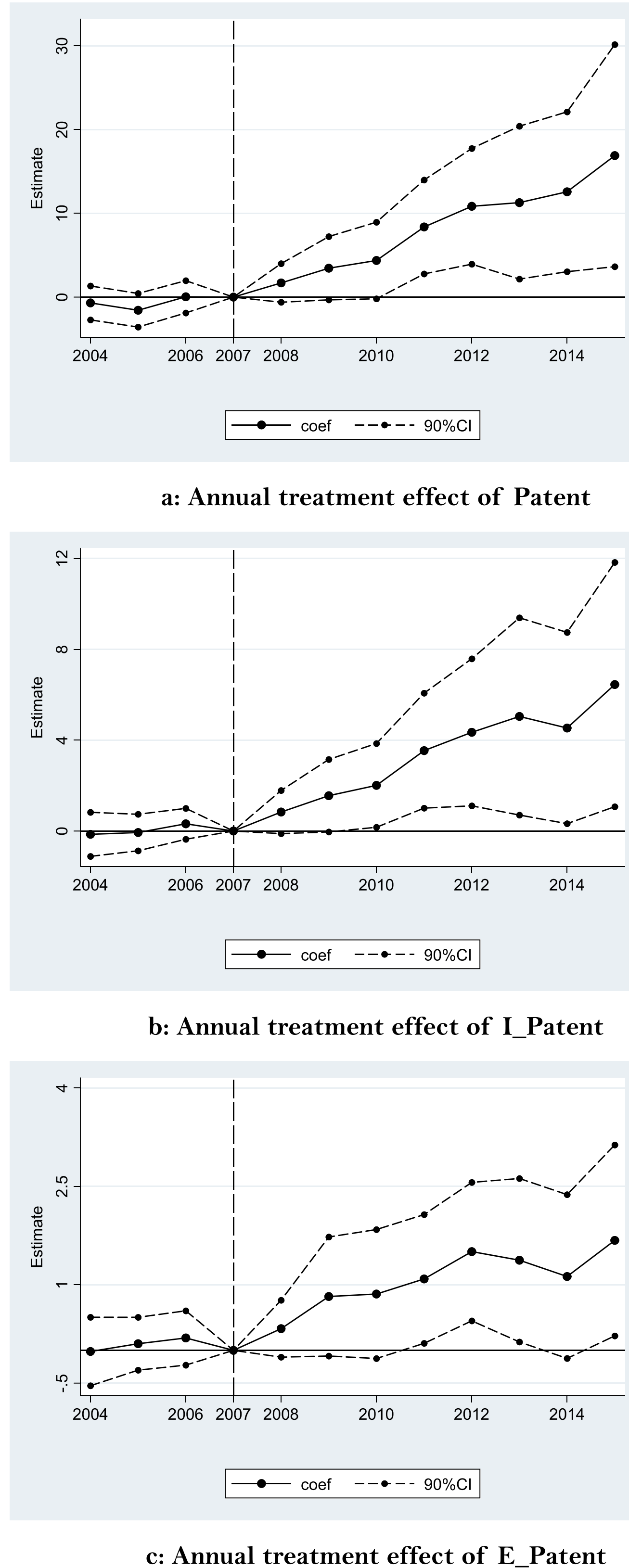

Fig. 2. a) Annual treatment effect of Patent. b) Annual treatment effect of I_Patent. c) Annual treatment effect of E_Patent.

Table 3
Average treatment effects of DDD estimates.

Variables	Patent (1)	I_Patent (2)	E_Patent (3)
Treat × time × SO_2	20.648***	7.853***	2.642***
	(4.868)	(2.229)	(0.628)
Controls	Y	Y	Y
Firm fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Constant	−135.344**	−48.246*	−21.242***
	(53.892)	(24.701)	(6.873)
Observations	4954	4954	4954
R-squared	0.605	0.542	0.486

Note: All the control variables are the same as described in Eq. (1). Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4
IV estimation results.

Variables	First-stage (1) Treat × time	Second-stage Patent (1)	I_Patent (2)	E_Patent (3)
Distance × time	−0.069***	9.298**	3.142*	1.100*
	(0.006)	(4.406)	(1.746)	(0.641)
Controls	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Constant	−4.60***	−95.609	−59.533*	−16.105**
	(0.700)	(64.981)	(31.407)	(7.903)
Observations		2736	2736	2736
R-squared		0.524	0.491	0.471
F statistics	632.96			

Note: All the control variables are the same as described in Eq. (1). Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

estimate the following model:

$$Y_{it} = \theta_0 + \theta_1 Treat_i \times Time_t + \theta_2 X_{it} + \delta_i + \mu_t + \varepsilon_{it}, \quad (4)$$

where i indexes cities (or provinces) and t indexes years. We measure SO_2 emissions (environmental performance) and industrial GDP (economic performance) at the city or province level. The coefficient θ_1 captures the average changes in environmental or economic performance in cities (or provinces) relative to the control group during the policy period. X_{it} controls for an additional set of covariates including fixed assets, investment in technology, industry employees, FDI and social consumption, and these control variables are lagged one year to avoid two-way causation (Rubashkina et al., 2015; Xie et al., 2017). The location fixed effects, δ_i, control for the permanent heterogeneity across cities (or provinces) whereas the year fixed effects, μ_t, control for year-specific shocks such as macroeconomic shocks that are common to both pilot areas and non-pilot areas.

Table 7 presents the results of the emissions trading policy effects on environmental and economic performance. Column 1 provides the results of SO_2 emissions where the dependent variable is measured at the city level, while column 2 uses province-level measures. The results show that the SO_2 emissions trading policy is effective in reducing SO_2 emissions. For the economic performance, as shown in columns 3 and 4, this policy significantly increases the industrial GDP relative to the control group. These results provide evidences that a market-based emissions trading program could result in a win-win achievement in both environmental protection and economic growth (Albino et al., 2014).

6. Conclusion

This paper empirically examines the impacts of China's SO_2 emissions trading program on firm innovation by exploring the unique setup of the program. Specifically, based on the panel data of China's publicly traded firms from 2004 to 2015, we adopt the DID model to examine the innovation effects of the SO_2 emissions trading pilot policy. The results indicate that the SO_2 emission trading program promotes 28.3% more patent applications per year and 22.3% more environmental patent applications of the regulated firms in pilot areas compared to nonpilot firms. In heterogeneity analysis, the policy performs better in areas with stricter environmental enforcement. Furthermore, our results show that the emissions trading program could simultaneously reduce SO_2 emissions and promote industrial growth in the pilot areas. Overall, our results indicate that the SO_2 ETS can promote the technological and environmental innovation of regulated firms in developing countries, which is conducive to promoting the sustainable development of the environment and economy.

We further emphasize the following policy recommendations, which will be critical for improving the policy effects. First, our results show that the emissions trading program has a positive impact on firm innovation and environmental innovation, and further analysis results show that the program decreases SO_2 emissions and simultaneously promotes industrial growth in pilot areas. These empirical evidences indicate the effectiveness of such policy even in developing country context, which is encouraging news as many fast-growing developing countries are experiencing the worst air pollution in the world and lack experience in addressing them. Therefore, the government could further extend these experiences to more regions, more industries to use such market-based policy to effectively reduce SO2 emissions. In addition, China's pilot policy offers support and reference for developing countries to use the emissions trading program to address serious environmental challenge and the tradeoff between environmental quality and economic growth.

Table 5
Other robustness checks.

Variables	Ruling out firm avoidance behavior Patent (1)	I_Patent (2)	E_Patent (3)	Poisson model Patent (4)	I_Patent (5)	E_Patent (6)
Treat × Time	10.626***	4.018**	1.166**	0.499**	0.758***	0.495*
	(3.868)	(1.659)	(0.505)	(0.239)	(0.213)	(0.282)
Controls	Y	Y	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Constant	−84.530	−49.795	−13.492*	−24.379***	−29.316***	−27.341***
	(69.925)	(31.927)	(7.572)	(4.138)	(4.307)	(4.470)
Observations	2556	2556	2556	2736	2736	2736
R-squared	0.527	0.493	0.474			

Note: All the control variables are the same as described in Eq. (1). Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6
Heterogeneity analysis.

Variables	Higher environment enforcement			Lower environment enforcement		
	Patent	I_Patent	E_Patent	Patent	I_Patent	E_Patent
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Time	11.677**	3.632*	1.152*	1.656	1.586	−0.134
	(4.814)	(2.031)	(0.661)	(3.497)	(1.997)	(0.406)
Controls	Y	Y	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Constant	−152.077	−110.987	−16.617	−109.073**	−62.632**	−21.546***
	(210.511)	(84.949)	(23.605)	(55.132)	(27.149)	(7.252)
Observations	1332	1332	1332	1404	1404	1404
R-squared	0.638	0.635	0.570	0.549	0.468	0.531

Note: All the control variables are the same as described in Eq. (1). Standard errors in parentheses are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7
Impact of emissions trading policy on SO_2 and industry GDP.

VARIABLES	City-level SO_2 emission (1)	Province-level SO_2 emission (2)	City-level Ind_GDP (3)	Province-level Ind_GDP (4)
Treat × Time	−0.716**	−6.840**	0.573**	8.372**
	(0.301)	(3.099)	(0.223)	(3.374)
Investment	−0.018	−0.106*	0.341***	0.258***
	(0.048)	(0.061)	(0.054)	(0.077)
Technology	−0.623	−2.225	10.289***	−0.892
	(1.945)	(4.826)	(2.429)	(4.973)
Employee	−0.515	−0.190	5.988***	9.118**
	(0.948)	(1.947)	(2.116)	(3.734)
FDI	0.235	0.422	−0.105	−0.687
	(0.323)	(0.689)	(0.310)	(0.830)
Consumption	−0.100	−0.066	0.404***	0.472**
	(0.067)	(0.107)	(0.091)	(0.191)
Province/City fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Constant	19.335***	13.868***	1.391*	−19.869***
	(0.571)	(2.944)	(0.806)	(3.406)
Observations	3069	330	3069	330
R-squared	0.842	0.964	0.978	0.987

Note: For columns 1 and 3, standard errors in parentheses are clustered at the city level; for columns 2 and 4, standard errors are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.All the data comes from China *City Statistical Yearbook* (2005–2016). Due to missing data, Tibet, Hong Kong, Macau, Taiwan were excluded from the analysis.

Second, our results show that the innovation effects of the policy are better in areas with stricter environmental enforcement, which indicate that the effective implementation of such policy requires sound environmental supervision and enforcement. Therefore, the government should speed up the legislation on the SO_2 ETS to ensure the effective operation of the emission trading. More importantly, strict emission monitoring system and data quality are the key and basic aspects of the SO_2 emissions trading system. Therefore, the government should establish a national pollution inventory and effectively monitor the emissions of enterprises. In addition, transparent and independent reporting of SO_2 emissions is crucial (Zhang et al., 2014), so the independent verification of annual emissions reports needs to be strengthened to improve the accuracy and credibility of emissions trading.

Third, our study provides some practical policy design experiences based on China's SO_2 ETS pilot policy. For example, compared with EU ETS design features, China's SO_2 ETS was implemented in a single country context, which has strong consistency in policy design, such as quota allocation and trading system etc. Moreover, the emissions caps in the pilot areas are de facto stringent caps rather than absolute emissions caps as in the EU ETS, i.e., China's emissions caps adopted by the pilot areas are determined by benchmarking and growth rates (Jotzo and Löschel, 2014). Additionally, each province establishes an emissions trading centre to facilitate emission trading among firms and dynamically regulate the allowance price to retain the effective operation of the market by the reserved quotas. These practical experiences provide a reference for other ETSs implemented worldwide, which is conducive to continuously improving the effects of ETSs.

Future research can proceed in the following directions. First, understanding the Pollution Haven Hypothesis induced by such policy by examining foreign direct investment and export behavioral changes, or the impact of regulation on firm location would be an interesting direction. Second, while our study provides evidence of the weak Porter Hypothesis, future research could investigate whether the strong version of the Porter Hypothesis is supported by examining firm competitiveness and performance (Cohen and Tubb, 2018). Future studies could extend to a comparison of the different effects of market-based emissions trading policy and command-and-control environmental regulations, such as the Two Control Zones (TCZ) policy.

CRediT authorship contribution statement

Shenggang Ren: Conceptualization, Methodology, Supervision, Project administration, Validation, Resources, Funding acquisition. **Yucai Hu:** Data curation, Software, Formal analysis, Writing - original draft, Writing - review & editing. **Jingjing Zheng:** Software, Writing - original draft, Data curation, Data curation. **Yangjie Wang:** Methodology, Funding acquisition, Conceptualization.

Acknowledgments

This research is supported by the National Natural Science Foundation of China (71974205), and by the Key Program of the National Natural Science Foundation of China (71991483), and by General Topics of the Hunan Province Social Science Evaluation Committee (XSP19YBZ093). We thank Michael Roach for constructive comments.

Appendix

Tables A1 and A2

Table A1
Trading Centres and Aggregate Statistics By Province.

Pilot provinces (1)	Launch of the trading centre (2)	Benchmark price (1000 Yuan/ton) (3)	Real price (10,00 yuan/ton) (4)	Accumulated transactions (100 million Yuan) (5)
Jiangsu	2009–09	2.24	19.2	4.23, by Dec., 2016
Zhejiang	2009–03	2	12.4	7.73, by Jun., 2014
Hubei	2009–03	3.9	9.3	0.26, by Dec., 2014
Chongqing	2009–11	4.9	13	2.96, by Jun., 2016
Hunan	2012–7	15	15	2.02, by Jun., 2017
Inner Mongolia	2010–09	2.5	2.5	2.1, by Dec., 2016
Hebei	2011–10	5	5	0.61, by Dec., 2013
Shanxi	2011–10	18	18	18, by Dec., 2016
Henan	2012–12	4.9	4.9	1.11, by Nov., 2013
Shaanxi	2010–06	6	11	7.53, by Dec., 2016

Note:Data is compiled from published information from the trading centre of each pilot province. The data for Tianjin is unavailable.

Table A2
Variable definitions.

Variable	Code	Variable definition
Treat	Treat	A dummy variable, equals 1 if a firm is located in the pilot areas of the SO_2 ETS policy and equals 0 otherwise. The pilot areas include Jiangsu, Zhejiang, Tianjin, Hubei, Hunan, Henan, Shanxi, Chongqing, Shaanxi, Hebei, and Inner Mongolia. The other 20 provinces are considered as non-pilot areas.
Time	Time	Time equals 1 for every year after 2007, otherwise it equals 0.
SO_2group	SO_2	A dummy variable, 1 for SO_2 emission firm, 0 for non SO_2 emission firm.
Technological Innovation	Patent	The number of new patent applications by a firm in each year.
	I_Patent	The number of new invention patent applications by a firm in each year (piece).
Environmental Innovation	E_Patent	The number of new environmental patent applications by a firm in each year (piece).
Firm Size	Size	The logarithm of total assets in a year.
Firm Age	Age	The number of years since a firm was founded.
SOE	SOE	A dummy variable, 1 for SOEs, 0 for others.
ROA	ROA	Net income / total asset.
Leverage	Leverage	The ratio of corporate total liabilities to total assets.
R&D	R&D	R&D expenses / Total Assets × 100%
Export	Export	A dummy variable, 1 for export firm, 0 for others.
HHI	HHI	The Herfindahl-Hirschman Index (HHI) constructed at the two-digit SIC level using sales revenue.
Per GDP	Per_GDP	The logarithm of provincial GDP at the end of each year divided by the population.
Environment Enforcement	Enforce	The logarithm of the number of environmental administrative punishment cases.
Market Share	Share	The ratio of firm sales to national industry sales in each year (%).
SO_2 emission	SO_2	Total SO_2 emissions per province (city) in a year (10 thousand ton).
Industrial GDP	Ind_GDP	Industrial GDP per province (city) in a year (10 billion RMB)
Assets invest	Investment	Fixed asset investment per province (city) in a year (10 billion RMB)
Technology	Technology	Investment in technology per province (city) in a year(10 billion RMB)
Employee	Employee	Number of industry employees per province (city) in a year (1000,000)
FDI	FDI	Foreign direct investment per province (city) in a year (10 billion RMB)
Social consumption	Consumption	The total retail sales of social consumer goods per province (city) in a year (10 billion RMB)

References

Ardito, L., Messeni Petruzzelli, A., Pascucci, F., Peruffo, E., 2019a. Inter-firm R&D collaborations and green innovation value: the role of family firms' involvement and the moderating effects of proximity dimensions. Bus. Strateg. Environ. 28 (1), 185–197.

Ardito, L., Petruzzelli, A.M., Ghisetti, C., 2019b. The impact of public research on the technological development of industry in the green energy field. Technol. Forecast. Soc. Change 144, 25–35.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., Reenen, J.V., 2016. Carbon taxes, path dependency, and directed technical change: evidence from the auto industry. J. Polit. Econ. 124 (1), 1–51.

Albino, V., Ardito, L., Dangelico, R.M., Messeni Petruzzelli, A., 2014. Understanding the development trends of low-carbon energy technologies: a patent analysis. Appl. Energy 135, 836–854.

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

Ambec, S., Cohen, M.A., Elgie, S., Lanoie, P., 2013. The Porter hypothesis at 20: can environmental regulation enhance innovation and competitiveness? Rev. Environ. Econ. Policy 7 (1), 2–22.

Anderson, B., Di Maria, C., 2011. Abatement and allocation in the pilot phase of the EU ETS. Environ. Resour. Econ. 48 (1), 83–103.

Anger, N., Oberndorfer, U., 2008. Firm performance and employment in the EU emissions trading scheme: an empirical assessment for Germany. Energy Policy 36 (1), 12–22.

Antonioli, D., Mancinelli, S., Mazzanti, M., 2013. Is environmental innovation embedded within high-performance organisational changes? The role of human resource management and complementarity in green business strategies. Res. Policy 42 (4), 975–988.

Ardito, L., Messeni Petruzzelli, A., Albino, V., 2016. Investigating the antecedents of general purpose technologies: a patent perspective in the green energy field. J. Eng. Technol. Manag. 39, 81–100.

Bansal, S., Gangopadhyay, S., 2003. Tax/subsidy policies in the presence of environmentally aware consumers. J. Environ. Econ. Manag. 45 (2, Supplement), 333–355.

Bel, G., Joseph, S., 2015. Emission abatement: untangling the impacts of the EU ETS and the economic crisis. Energy Econ. 49, 531–539.

Boeing, P., 2016. The allocation and effectiveness of China's R&D subsidies - evidence from listed firms. Research Policy 45 (9), 1774–1789.

Borghesi, S., Cainelli, G., Mazzanti, M., 2015. Linking emission trading to environmental innovation: evidence from the Italian manufacturing industry. Res. Policy 44 (3), 669–683.

Bronzini, R., Piselli, P., 2016. The impact of R&D subsidies on firm innovation. Res. Policy 45 (2), 442–457.

Brunnermeier, S.B., Cohen, M.A., 2003. Determinants of environmental innovation in US

manufacturing industries. Journal of environmental economics and management 45 (2), 278–293.
Cai, X., Lu, Y., Wu, M., Yu, L., 2016. Does environmental regulation drive away inbound foreign direct investment? Evidence from a quasi-natural experiment in China. J. Dev. Econ. 123, 73–85.
Calel, R., Dechezleprêtre, A., 2016. Environmental policy and directed technological change: evidence from the European carbon market. Rev. Econ. Stat. 98 (1), 173–191.
Chakraborty, P., Chatterjee, C., 2017. Does environmental regulation indirectly induce upstream innovation? New evidence from India. Res. Policy 46 (5), 939–955.
Chang, X., Fu, K., Low, A., Zhang, W., 2015. Non-executive employee stock options and corporate innovation. J. Financ. Econ. 115 (1), 168–188.
Chang, Y.C., Wang, N., 2010. Environmental regulations and emissions trading in China. Energy Policy 38 (7), 3356–3364.
Chung, S., 2014. Environmental regulation and foreign direct investment: Evidence from South Korea. Journal of Development Economics 108, 222–236.
Chemmanur, T.J., Tian, X., 2018. Do antitakeover provisions spur corporate innovation? A regression discontinuity analysis. Jo. Financ. Quant. Anal. 53 (3), 1163–1194.
Cho, S.Y., Kim, S.K., 2017. Horizon problem and firm innovation: the influence of CEO career horizon, exploitation and exploration on breakthrough innovations. Res. Policy 46 (10), 1801–1809.
Clò, S., Ferraris, M., Florio, M., 2017. Ownership and environmental regulation: evidence from the European electricity industry. Energy Econ. 61, 298–312.
Cohen, M.A., Tubb, A., 2018. The impact of environmental regulation on firm and country competitiveness: a meta-analysis of the porter hypothesis. J. Assoc. Environ. Resour. Econ. 5 (2), 371–399.
Costantini, V., Mazzanti, M., 2012. On the green and innovative side of trade competitiveness? The impact of environmental policies and innovation on EU exports. Res. Policy 41 (1), 132–153.
Damanpour, F., 1987. The adoption of technological, administrative, and ancillary innovations: impact of organizational factors. J. Manag. 13 (4), 675–688.
Dechezleprêtre, A., Sato, M., 2017. The impacts of environmental regulations on competitiveness. Rev. Environ. Econ. Policy 11 (2), 183–206.
del Río González, P., 2009. The empirical analysis of the determinants for environmental technological change: a research agenda. Ecol. Econ. 68 (3), 861–878.
Ellerman, A.D., Buchner, B.K., 2008. Over-Allocation or abatement? A preliminary analysis of the EU ETS based on the 2005–06 emissions data. Environ. Resour. Econ. 41 (2), 267–287.
Fowlie, M., 2010. Emissions trading, electricity restructing, and investment in pollution abatement. Am. Econ. Rev. 100 (3), 837–869.
Fredriksson, P.G., Vollebergh, H.R., Dijkgraaf, E., 2004. Corruption and energy efficiency in OECD countries: theory and evidence. Journal of Environmental Economics and management 47 (2), 207–231.
Frondel, M., Horbach, J., Rennings, K., 2008. What triggers environmental management and innovation? Empirical evidence for Germany. Ecol. Econ. 66 (1), 153–160.
Gagelmann, F., Frondel, M., 2005. The impact of emission trading on innovationscience fiction or reality? European Environment 15 (4), 203–211.
Greenstone, M., Hanna, R., 2014. Environmental regulations, air and water pollution, and infant mortality in India. Am. Econ. Rev. 104 (10), 3038–3072.
Grubb, M., Azar, C., Persson, U.M., 2005. Allowance allocation in the European emissions trading system: a commentary. Clim. Policy 5 (1), 127–136.
Guan, J., Yam, R.C.M., 2015. Effects of government financial incentives on firms' innovation performance in China: evidences from Beijing in the 1990s. Res. Policy 44 (1), 273–282.
Guo, D., Guo, Y., Jiang, K., 2016. Government-subsidized R&D and firm innovation: evidence from China. Res. Policy 45 (6), 1129–1144.
Hagedoorn, J., Cloodt, M., 2003. Measuring innovative performance: is there an advantage in using multiple indicators? Res. Policy 32 (8), 1365–1379.
Hall, B.H., Ziedonis, R.H., 2001. The patent paradox revisited: an empirical study of patenting in the U.S. semiconductor industry, 1979–1995. RAND J. Econ. 32 (1), 101–128.
Hanna, R., 2010. US environmental regulation and FDI: evidence from a panel of US-Based multinational firms. Am. Econ. J. Appl. Econ. 2 (3), 158–189.
Hoffmann, V.H., 2007. EU ETS and investment decisions: the case of the German electricity industry. Eur. Manag. J. 25 (6), 464–474.
Horbach, J., 2008. Determinants of environmental innovation—new evidence from German panel data sources. Res. Policy 37 (1), 163–173.
Horbach, J., Rammer, C., Rennings, K., 2012. Determinants of eco-innovations by type of environmental impact—the role of regulatory push/pull, technology push and market pull. Ecol. Econ. 78, 112–122.
Huang, R., Chen, D., 2015. Does environmental information disclosure benefit waste discharge reduction? Evidence from China. J. Bus. Ethics 129 (3), 535–552.
Inoue, E., Arimura, T.H., Nakano, M., 2013. A new insight into environmental innovation: does the maturity of environmental management systems matter? Ecol. Econ. 94, 156–163.
Jaffe, A., Newell, R., Stavins, R., 2002. Environmental policy and technological change. Environ. Resour. Econ. 22 (1), 41–70.
Jaffe, A.B., Palmer, K., 1997. Environmental regulation and innovation: a panel data study. Rev. Econ. Stat. 79 (4), 610–619.
Johnstone, N., Haščič, I., Popp, D., 2010. Renewable energy policies and technological innovation: evidence based on patent counts. Environ. Resour. Econ. 45 (1), 133–155.
Jotzo, F., Löschel, A., 2014. Emissions trading in China: emerging experiences and international lessons. Energy Policy 75, 3–8.
Kemp, R., Pearson, P., 2007. Final Report MEI Project About Measuring Eco-Innovation. Final Report MEI Project About Measuring Eco-Innovation 10. UM Merit, Maastricht, pp. 2.
Kesidou, E., Demirel, P., 2012. On the drivers of eco-innovations: empirical evidence from the UK. Res. Policy 41 (5), 862–870.
Lange, I., Bellas, A., 2005. Technological change for sulfur dioxide scrubbers under market-based regulation. Land Econ. 81 (4), 546–556.
Li, D., Huang, M., Ren, S., Chen, X., Ning, L., 2016. Environmental legitimacy, green innovation, and corporate carbon disclosure: evidence from CDP China 100. J. Bus. Ethics (1), 1–16.
Li, R., Ramanathan, R., 2018. Exploring the relationships between different types of environmental regulations and environmental performance: evidence from China. J. Clean. Prod. 196, 1329–1340.
Marchi, V.D., 2012. Environmental innovation and R&D cooperation: empirical evidence from Spanish manufacturing firms. Res. Policy 41 (3), 614–623.
Martin, R., Muûls, M., Wagner, U., 2011. Climate Change, Investment and Carbon Markets and Prices: Evidence from Manager Interviews. Climate Strategies, Carbon Pricing for Low-Carbon Investment Project, pp. 2011.
OECD, 2005. Oslo Manual Guidelines for Collecting and Interpreting Innovation Data. Organisation for Economic Co-operation and Development: Statistical Office of the European Communities, Paris.
Pavitt, K., 1984. Sectoral patterns of technical change: towards a taxonomy and a theory. Res. Policy 13 (6), 343–373.
Petruzzelli, A.M., Dangelico, R.M., Rotolo, D., Albino, V., 2011). Organizational factors and technological features in the development of green innovations: Evidence from patent analysis. Innovation 13 (3), 291–310.
Popp, D., 2003. Pollution control innovations and the Clean Air Act of 1990. J. Policy Anal. Manag. 22 (4), 641–660.
Porter, M.E., 1991. Essay: America's Green Strategy 264 Scientific American.
Porter, M.E., Linde, C.V.D., 1995. Toward a new conception of the environment-competitiveness relationship. J. Econ. Perspect. 9 (4), 97–118.
Rennings, K., 2000. Redefining innovation—eco-innovation research and the contribution from ecological economics. Ecol. Econ. 32 (2), 319–332.
Rogge, K.S., Schneider, M., Hoffmann, V.H., 2011. The innovation impact of the EU Emission Trading System—findings of company case studies in the German power sector. Ecol. Econ. 70 (3), 513–523.
Rubashkina, Y., Galeotti, M., Verdolini, E., 2015. Environmental regulation and competitiveness: empirical evidence on the Porter Hypothesis from European manufacturing sectors. Energy Policy 83, 288–300.
Sapkota, P., Bastola, U., 2017. Foreign direct investment, income, and environmental pollution in developing countries: panel data analysis of Latin America. Energy Econ. 64, 206–212.
Stock, G.N., Greis, N.P., Fischer, W.A., 2002. Firm size and dynamic technological innovation. Technovation 22 (9), 537–549.
Taylor, M.R., 2012. Innovation under cap-and-trade programs. Proc. Natl. Acad. Sci. USA 109 (13), 4804–4809.
Tomás, R.A.F., Ramôa Ribeiro, F., Santos, V.M.S., Gomes, J.F.P., Bordado, J.C.M., 2010. Assessment of the impact of the European CO_2 emissions trading scheme on the Portuguese chemical industry. Energy Policy 38 (1), 626–632.
Wagner, M., 2007. On the relationship between environmental management, environmental innovation and patenting: evidence from German manufacturing firms. Res. Policy 36 (10), 1587–1602.
Xie, R.-h., Yuan, Y.-j., Huang, J.-j, 2017. Different types of environmental regulations and heterogeneous influence on “Green” Productivity: evidence from China. Ecol. Econ. 132, 104–112.
Xu, J., Tan, X., He, G., Liu, Y., 2019. Disentangling the drivers of carbon prices in China's ETS pilots—An EEMD approach. Technol. Forecast. Soc. Change 139, 1–9.
Yang, Z., Fan, M., Shao, S., Yang, L., 2017. Does carbon intensity constraint policy improve industrial green production performance in China? A quasi-DID analysis. Energy Econ. 68, 271–282.
Zhang, D., Karplus, V.J., Cassisa, C., Zhang, X., 2014. Emissions trading in China: progress and prospects. Energy Policy 75, 9–16.

Shenggang Ren (PhD, Fudan University) is a Professor of School of Business at Central South University. His-main research areas are innovation management, industry and environmental policy research. His-refereed articles have been published in a variety of journals including Journal of Business Ethics, Journal of Business Research and Business Strategy and the Environment.

Email: renshenggang1975@csu.edu.cn.

Yucai Hu (corresponding author) is a PhD candidate in the School of Business Central South University. His-main research areas are innovation management and environmental policy research.

Email: 344978605@qq.com.

Jingjing Zheng is a PhD candidate in the School of Business Central South University. His-main research areas are innovation management and environmental policy research.

Yangjie Wang is an associate professor in the School of Business at Central South University. His-main research areas are innovation management and environmental policy research.