The Impacts of Carbon Pricing on Firm Competitiveness: Evidence from the Regional Carbon Market Pilots in China*

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Abstract

We examine the impacts of China's unconventional emission trading system (ETS), a rate-based tradable performance standard (TPS), on firm competitiveness. Our analysis takes advantage of the quasi-natural experiment created by China's regional ETS pilots and firm-level data on innovation and financial performance. We find that ETS directs firm innovation towards climate technologies, increasing the share of low-carbon patents by 0.021 percentage points and the total number of low-carbon patents by 20.5 percent. Allowance trading and price play an instrumental role in improving the intensity and quality of innovation. Furthermore, we find no evidence that ETS harms firm profitability.

Keywords: Emission Trading System, Innovation, Firm Competitiveness.

JEL Classification: L51, Q55, O3

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1 Introduction

The major economies are resorting to carbon pricing, mainly emissions trading system (ETS), to achieve cost-effective climate mitigation. World Bank (2020) reports that 31 jurisdictions in the world have implemented or scheduled carbon ETS.[1] The flexible market-based climate policy gives more freedom to firms on their paths of compliance, which induces carbon-reducing innovation. The evidence has been well documented in developed countries such as the EU (Martin, Muûls, and Wagner, 2012; Borghesi, Cainelli, and Mazzanti, 2015; Calel and Dechezleprêtre, 2016; Calel, 2020) and the US (Taylor, 2012). Little is known in China, by far the world's largest greenhouse gas emitter (Cui, Zhang, and Zheng, 2018; Zhu et al., 2019). As China is tapping the carbon market for emission controls, understanding the economic impacts of ETS on firms will be instrumental for China to make a more aggressive and meaningful climate commitment.

China's regional ETS pilots provide us with an excellent quasi-natural experiment to identify the ETS effect on firm competitiveness with a focus on innovation activities. First, the regional pilots enable us to construct treatment and control groups to compare the performances of regulated and unregulated firms. Second, the regional pilots are implemented in two phases: the ETS rules were set up in 2011-2012 and allowance trading was implemented during 2013-2016. This allows us to study the importance of explicit carbon price and allowance trading in the post-treatment stage. Last but not least, what distinguishes China's ETS from the EU ETS is that China adopts the tradable performance standard (TPS) approach (Goulder and Morgenstern, 2018; Pizer and Zhang, 2018; Goulder et al., 2019). Unlike the cap and trade programs, TPS is an intensity-based instrument without an absolute emission cap. As a consequence, TPS could not be efficient (Holland, Hughes, and Knittel, 2009) and it poses a weaker regulatory pressure than the cap and

[1] The EU ETS, launched in 2005, is the first and largest major carbon emission trading system in the world. Although there is no national ETS in the US, 9 Northeast states formed the Regional Greenhouse Gas Initiative (RGGI) in 2009 and California launched the cap and trade program in 2012. More states are in various stages of adopting ETS including Washington, Virginia, Pennsylvania, and Oregon.

trade since the compliance can be achieved through reducing emissions and/or increasing outputs (Fischer and Newell, 2008; Boom and Dijkstra, 2009). Milliman and Prince (1989) argues that performance standard provides less incentives for innovation than market-based instruments do. This paper will test the effect of TPS on stimulating innovation.

Taking advantage of the regulatory variations across regions and sectors over time, we employ a difference-in-difference-in-differences (DDD) approach to assess the impacts of ETS on firms' innovation and financial performance. We have assembled a unique dataset of economic and innovation activities for 2,142 Chinese publicly listed firms and their subsidiaries between 2003 and 2016. The data pertain to the public firms in the manufacturing and utility sectors, integrating detailed firm-level information about patents granted in all technological fields, R&D expenditure, and economic fundamentals. To better measure the regulatory exposure of a firm, we retrieve the corporate tree for each listed firm, including a list of subsidiary firms, shareholdings, sector information, geographic location, and patents. Utilizing the detailed corporate tree information, we construct various indicators to measure a listed firm's exposure to ETS. In the end, we have 21,531 firm-year observations associated with 2,142 unique listed firms and their 57,842 subsidiaries.

We demonstrate unambiguous evidence that China's ETS accelerates innovation of carbon-reducing technologies. Specifically, it increases the share of low-carbon patents by 0.021 percentage points and an increase of 20.5 percent in patent counts. The effect is more pronounced for high-quality patents than for incremental ones.[2] We find that allowance trading and explicit carbon price played an instrumental role in stimulating innovation. Particularly, we show that a higher carbon price creates more incentives for low-carbon patenting. A higher carbon price also increases the quality of innovation measured by patent citations. Furthermore, we find no evidence that ETS has a negative impact on firm financial performance, likely due to the beneficial effect of triggered innovation. These results survived numerous robustness checks regarding alternative specifications

[2]We define invention patents as high-quality patents and utility patents as incremental ones.

and potential confounding environmental, energy, and industrial policies.

This paper contributes to the growing literature on the effect of market-based instruments in inducing innovation of environmentally friendly technologies.[3] This is the first paper that identifies the causal effects of TPS on firm innovation and financial performance using the regional ETS pilots in China. Our analysis shows that China's ETS is on par with the EU ETS in terms of innovation stimulation. To put it in context, Calel and Dechezleprêtre (2016)'s findings suggest a 10 percent increase in low-carbon patenting for EU firms during the 1978-2009 period, and the follow-up study by Calel (2020) indicates roughly 20 to 30 percent increase in low-carbon patenting and R&D spending for regulated British firms during the 2000-2012 period.

In addition, this paper is the first attempt to sort out the entire corporate tree structure of publicly listed firms in a large economy. Considering that a firm may have subsidiaries operating in regions or sectors with and without ETS, we account for firms' corporate tree to better measure firm regulatory exposure (Hanna, 2010; Giroud and Mueller, 2015, 2019; Cui and Moschini, 2020). In so doing, this paper improves the assessment of firms' exposure to climate policy. Furthermore, we make substantial data contributions by constructing a unique China Patent Project, analogous to the NBER Patent Data Project.[4] Our data project that integrates detailed patents and citations of 2,142 Chinese publicly listed firms and their subsidiaries during the 2003 to 2016 period can be applied to a wild variety of research in firm innovation.

Our analysis provides important insights for addressing China's challenge of limiting its ever-increasing carbon emissions without sacrificing economic growth. On the

[3]Pioneering work has examined how energy price leads to the invention of energy-saving technologies (Newell, Jaffe, and Stavins, 1999; Jaffe, Newell, and Stavins, 2002; Popp, 2002; Linn, 2008; Johnstone, Haščič, and Popp, 2010) and how environmental regulation incentivizes innovation and diffusion of pollution abatement technologies (Popp, 2003, 2006; Dechezleprêtre and Glachant, 2014). A burgeoning literature has explored the effect of ETS in the EU and US (Martin, Muûls, and Wagner, 2012; Taylor, 2012; Borghesi, Cainelli, and Mazzanti, 2015; Calel and Dechezleprêtre, 2016; Borenstein et al., 2019; Calel, 2020).

[4]The NBER Patent Data Project provides patents and citations of listed firms during the 1976-2006 period. The dataset is matched between United States Patent and Trademark Office (USPTO) patents to the North America Compustat data at Wharton Research Data Services.

one hand, China has pledged to peak its carbon emissions by 2030 and aim for carbon neutrality by 2060. On the other hand, China has set an ambitious economic target to reach high-income status by 2035 and become a mid-level, high-income economy by 2050. Industrial competitiveness is the major concern for China to comply with its climate commitment. Our results suggest that as China tightens its regulation on carbon emissions, the innovation induced by carbon pricing can mitigate the cost of compliance. Under the current level of the carbon price in China ($4.2/ton), the innovation induced by ETS contributes to a 1.66 percent decrease in carbon intensity. Therefore, the market-based instrument can play a pivotal role in reducing abatement costs by inducing innovation.

The remainder of this paper is organized as followers. Section 2 introduces the background of China's regional ETS pilots. Section 3 provides empirical strategy addressing the identification challenges. Section 4 presents data sources, variables construction, and analysis of sample means. Section 5 shows empirical results and robustness checks. Section 6 concludes.

2 China's Regional ETS Pilots

China has gradually become active in global climate mitigation since it overtook the US to be the world's largest GHG emitter. In the 2009 Copenhagen Accord, China pledged to reduce its carbon intensity, measured by carbon emissions per unit of GDP, by 40 to 45 percent from 2005 levels by 2020. The carbon emission target was then embodied into the 12th Five-Year Plan (2011-2015), a blueprint for China's overall social and economic development. The endeavor in carbon emission reduction was further manifested in the late 2015 Paris Agreement. China committed to cut down its carbon intensity by 60 to 65 percent from 2005 levels by 2030 and peak carbon emissions around 2030. The recent pledge of carbon neutrality by 2060 further demonstrates China's long-term commitment to tackling the challenge of global climate change.

China has been relying on market-based instruments, especially ETS, to control carbon emissions cost-effectively. On October 29th of 2011, the National Development and Reform Commission (NDRC) formally approved the regional carbon market pilots in seven jurisdictions, including Beijing, Shanghai, Tianjin, Chongqing, Guangdong, Hubei, and Shenzhen.[5] The pilot regions are granted flexibility in designing their own carbon market rules following some general guidelines from NDRC. Specifically, each pilot has the discretion to determine covered sectors, emissions targets, allowance allocation, monitoring, reporting and verification (MRV), and compliance, while NDRC oversees the planning and development of ETS (Zhang, Wang, and Du, 2017). Table A1 in the Online Appendix provides a summary of ETS policies across pilots.

The seven pilots regulate a different set of sectors, covering the major emitters in both manufacturing and non-manufacturing industries. Except for Hubei, which uses energy consumption as the indicator, all other pilots use annual carbon emissions to determine the regulatory status of an entity. Most pilots set the threshold of annual emissions at 20kt, with Shenzhen adopting a lower threshold. Due to the differences in emissions and regulations, the total carbon allowances vary substantially across pilots. Guangdong has the largest carbon allowance (338Mt), while Shenzhen has the smallest one (30Mt). The shares of emissions covered by ETS range from 33 percent in Hubei to 60 percent in Tianjin.

Most pilots adopt both benchmarking and grandfathering approaches for allowance allocation, except that Chongqing only uses grandfathering. Beijing regulates new entrants by benchmarking while applying grandfathering to the existing entities. The allowance allocation in the other pilots depends on specific sectors covered, but benchmarking is usually applied in the power sector. Almost all pilots allocate allowances for free, while Guangdong and Shenzhen auction a small share of allowances up to 3 percent. Allowances are allocated on an annual basis, except for Shanghai, which allocated the allowances for the compliance period of 2013-2015 at one time. Allowances could only be

[5]Shenzhen is a part of Guangdong, but they joined in the regional carbon market pilots independently.

traded within the pilot but not across pilots. Finally, each pilot has established its MRV system but shares a similar protocol. Compliance is the norm. Noncompliance will result in a variety of penalties such as financial penalties, deduction of the excessive emission allowances, and recording in the business credit report systems.

China's ETS, including the regional ETS pilots and the national ETS, is in essence a rate-based TPS. Different from the cap and trade programs that set a limit on total emissions, the TPS regulator sets benchmarks for carbon emissions per unit of output and allows emitters to trade allowances.[6] In the cap and trade program, the allowance for a regulated entity is pre-determined in advance of the compliance period. Under the TPS in China's ETS, the regulator allocates allowances in two phases. At the beginning of a compliance period, a regulated entity is granted allowances based on its output in the previous compliance period, multiplied by the designated benchmark emissions-output ratio and an initial allocation factor, both of which are set by the regulator. At the end of the compliance period, a regulated entity could receive additional allowances sufficient to bring the ratio of total allowances to output over the entire period down to the specified benchmark emissions-output ratio. Thus, TPS tends to have less regulatory pressure on emitters than the cap and trade program does.

The unique design of China's regional ETS pilots provides a quasi-natural experiment for teasing out the causal relationship between ETS and firm competitiveness. Among 34 provincial-level jurisdictions in China, the ETS pilots include two provinces (i.e., Guangdong and Hubei), four municipalities (i.e., Beijing, Shanghai, Tianjin, and Chongqing), and one special economy zone (i.e., Shenzhen). Each jurisdiction determines to cover a different set of sectors. Since we observe firm-level low-carbon innovation and financial performance before and after the ETS, this allows us to compare the treatment and control groups using the triple differences approach taking advantage of variations across regions, sectors, and over time. Besides, the seven regional pilots were announced in late

[6]Some popular TPS programs include the US lead phase-down, California's Low Carbon Fuel Standard, and Corporate Average Fuel Economy.

2011, and the trading of emission allowances was initiated after 2013. By separating the ETS effects into two phases, we can investigate the mechanism of carbon ETS effect on firm competitiveness by isolating the effects of the carbon price and allowance trading.

3 Empirical Strategy

3.1 Main Model

A regulated firm has a flexible path of compliance with ETS. The firm can reduce emissions through fuel switching, energy conservation, and efficiency improvement in the production process. If the regulation is persistent, the firm has an incentive to engage in low-carbon innovation to achieve more cost-effective emission reductions in the long run. A plethora of empirical studies exploring the innovation effects of the EU and US ETS has mixed findings on the product and process innovation (Martin, Muûls, and Wagner, 2012; Borghesi, Cainelli, and Mazzanti, 2015), but the literature generally agrees that ETS can stimulate low-carbon patenting (Taylor, 2012; Calel and Dechezleprêtre, 2016; Calel, 2020).[7] However, it is largely unknown whether TPS has similar effects.

In this section, we propose an empirical framework to identify the causal effect of TPS on firms' low-carbon innovation. In terms of the policy intervention, China's regional ETS pilots regulate firms in the covered sectors in the seven jurisdictions after 2011. It is straightforward to adopt a DDD approach since the policy treatment varies by time,

[7]Based on responses from manager interviews, Martin, Muûls, and Wagner (2012) find no significant differences in clean process and product innovations between the EU ETS and non-EU ETS firms. Using a sample of Italian manufacturing firms from the 2006-2008 Community Innovation Survey dataset, Borghesi, Cainelli, and Mazzanti (2015) document a positive correlation between the EU ETS participation and environmental innovation aiming to reduce carbon emissions and improve energy efficiency. When it comes to the patenting activities, Calel and Dechezleprêtre (2016) examine the induced-innovation impact of the EU ETS on low-carbon patents during the 1979-2009 period. Their estimate finds that the EU ETS contributes to a 1 percent increase in the low-carbon patent. The recent study by Calel (2020) further shows that the EU ETS leads to greater low-carbon patenting and R&D spending among regulated British firms without affecting short-term reductions in the carbon intensity of output. In response to the two US nationwide cap and trade programs, Taylor (2012)'s findings suggest that innovators make investments in patenting activities.

sector, and region. For listed firm i in sector j from region r at year t, the baseline model that links ETS to firm low-carbon patenting is given by

$$Y_{ijrt} = \beta \text{ETS}_r \times \text{Sector}_j \times \text{Post}_t + \gamma' X_{it} + \lambda_i + \delta_{jt} + \eta_{rt} + \varepsilon_{ijrt}. \tag{1}$$

The DDD model above is estimated by ordinary least squares on the annual firm-level data. The outcome Y_{ijrt} refers to low-carbon patenting including shares and counts. The literature has been widely using patent as a proxy for firm innovation (Newell, Jaffe, and Stavins, 1999; Popp, 2002; Hall, Jaffe, and Trajtenberg, 2005; Johnstone, Haščič, and Popp, 2010; Taylor, 2012; Calel and Dechezleprêtre, 2016; Autor et al., 2020). Although not all innovation activities are patented, patenting is likely the most reliable information about firm innovation especially in China.

The policy treatment status of a listed firm depends on the sector, region, and time. We denote ETS_r as an indicator for pilot regions, which takes a value of one if r is one of the ETS pilots and zero otherwise. We designate Sector_j as a binary indicator for the covered sectors, equal to one for the covered sectors, and zero otherwise. We define $\text{Post}_t \equiv I(\text{Year} \geq 2011)_t$ as the ETS period dummy, equal to one if the year is 2011 and after, and zero otherwise. Thus, a regulated listed firm belongs to the covered sectors in one of the ETS regions after 2011. Correspondingly, β is the parameter of central interest reflecting the impact of ETS on the firms that are subject to the regulation. Other control variables, denoted by X_{it}, include time-varying firm attributes, such as firm age, asset, capital, revenue, and operating cost.

The firm-specific fixed effect, λ_i, is included to control for the firm-level unobservables that affect low-carbon patenting. The sector-by-year specific effect, δ_{jt}, accounts for the sector- and time-varying factors influencing firm innovation. The nationwide industrial policies that apply to all provinces, such as renewable energy subsidies, are controlled for by the sector-by-year fixed effect. This region-by-year specific effect, η_{rt}, accounts for the region- and time-varying factors influencing innovation. For example, the regional-level economic policies, which apply to all sectors, can be absorbed by the region-by-year fixed effect. Finally, ε_{ijrt} is an unobserved error term.

The identification is anchored on the underlying parallel trends assumption that the pre-existing differences in innovation for the treated and control groups are orthogonal to ETS. China's regional ETS pilots cover emission-intensive entities in the developed provinces or cities. There are systematical differences in innovation activities between the firms in treatment and control groups. Therefore, the fundamental identification assumption is that these differences are invariant across time for the DDD approach to yield a consistent estimate for the innovation impact of carbon ETS. To test the validity of this assumption, we perform a parallel trend test conditional on the observable characteristics that are relevant driving factors for innovation.

We are also concerned with the contemporary shocks that might differentially target the same treatment or control groups in the study period. Although this identification assumption cannot be tested directly, we conduct a set of robustness checks to assess the influence of some possible coinciding shocks. Below we discuss the strategies to address some potential threats to the validity of our identification.

The first threat is from the contemporary environmental policies that targeted overlapping regions. In 2013, the Ministry of Ecology and Environment[8] mandated Beijing, Tianjin, and Hebei (BTH)—the most polluted area in China—to dramatically heighten air pollution regulation, aiming at cleaning up regional air pollution especially $PM_{2.5}$. Since many air pollutants are co-emitted with carbon dioxide, the regional air pollution regulation might create an incentive of innovation similar to carbon ETS. To address this concern, we drop the firms from BTH in the sensitivity analysis.

The second threat is from the government subsidies on firm innovation. One policy is the nationwide favorite tax rate policy for firms with a high-tech status. Another

[8]Formerly the Ministry of Environmental Protection.

policy is the low-carbon special fund in Shenzhen. The third one is a nationwide energy subsidy policy related to photovoltaic (PV) technologies. To control for these potential confounding factors, we first drop the firms from Shenzhen throughout this paper due to little variations in the covered sectors in Shenzhen, because all manufacturing sectors in its jurisdiction are regulated. We then conduct several robustness checks by dropping the samples related to high-tech firms or PV patents.

The third threat is that the entry and exit of firms might change the composition of treatment and control groups. The exit is a less concern since the publicly listed firms in China are seldom delisted except for only a few cases.[9] In terms of entry, new firms with low-carbon technologies may select to locate in the ETS pilot regions. To address this concern, we remove all new firms entered after the start of ETS. A related concern is the relocation or shutdown of listed firms, but this is not observed in our data.

Besides DDD, we also adopt two alternative identification strategies. One is the difference-in-differences (DD) approach, and the other combines the propensity score matching (PSM) with the DD approach. The DD approach defines all the firms that are regulated under ETS as the treatment group, and the unregulated firms serve as the control group. This approach helps us test the stability of DDD results against alternative designations of the treatment group. Furthermore, in the PSM approach, we match ETS regulated firms with those unregulated firms based upon their pre-ETS economic characteristics. With this restricted matched sample, we adopt a variant of the DD method to examine the effect of ETS on low-carbon patenting activities.

[9]China Securities Regulatory Commission sets the entry-exit regulations for the stock markets in China. A firm with three consecutive years of fiscal deficit is subject to a suspension of listing and will face delisting if the deficit continues in the next six months. However, the prohibitive entry costs create an implicitly economic rent for a firm to hold the listed status, making it less likely to exit the stock market in response to environmental pressures. A total of 51 listed firms in China stock markets have been delisted by 2016.

3.2 Additional Specifications

In addition to the baseline model in Eq (1), we propose several additional specifications to further explore the underlying mechanism of how ETS stimulates innovation. First, we consider alternative measures of a listed firm's exposure to ETS. A large listed firm may have multiple subsidiaries. Depending on the sector, location, and time, these subsidiaries can have different treatment statuses. We define a listed firm's exposure to ETS as a function of its subsidiaries' exposures. As a result, below is a more generalized specification for evaluating the effect of ETS on firm innovation:

$$Y_{ijrt} = \beta \text{Exposure}_{it} + \gamma' X_{it} + \lambda_i + \delta_{jt} + \eta_{rt} + \varepsilon_{ijrt}, \tag{2}$$

where Exposure_{it} is an alternative measure of policy treatment. Following the approach proposed by Hanna (2010),[10] we consider listed firm i's exposure to ETS as the (weighted) average of all its subsidiaries' exposure:

$$\text{Exposure}_{it} = \frac{1}{N_{it}} \sum_{n=1}^{N_{it}} \left(w_{nt} \text{ETS}_{nr} \times \text{Sector}_{nj} \times \text{Post}_t \right), \tag{3}$$

where N_{it} is the number of subsidiaries for listed firm i; dummy variable ETS_{nr} designates subsidiary n located in one of ETS regions; binary indicator Sector_{nj} refers to subsidiary n's covered sector; w_{nt} is a weight, which is either one or the percentage of shares in a subsidiary.

Second, we also consider the fact that each ETS pilot has the discretion to determine its regulatory stringency. As a result, regional ETS pilots exhibit significant heterogeneity in terms of price signal strength. The different regulatory stringencies will affect a firm's intensity of policy treatment and thus create various incentives for innovation. Therefore,

[10] Hanna (2010) measures multi-plant firms' exposure to the local environmental policy by accounting for whether an affiliated plant is in the dirty sector and is located in non-attainment counties under the Clean Air Acts implemented by the US Environmental Protection Agency.

another variant of policy exposure is defined as follows:

$$\text{Exposure}_{it} = \frac{1}{N_{it}} \sum_{n=1}^{N_{it}} \left(w_{nt} \text{ETS}_{nr} \times \text{Sector}_{nj} \times \text{Post}_t \times \text{Price}_{rt} \right) . \tag{4}$$

In this form, Price_{rt} designates the region-specific price of carbon allowances, which is a proxy for the stringency of ETS regulation.

Third, China's regional ETS pilots are implemented in two phases: the pilots were officially announced in 2011 and the allowance trading started in 2013. Differentiating the ETS effect in the two periods leads to the following specification:

$$\begin{aligned} Y_{ijrt} = & \beta_1 \text{ETS}_r \times \text{Sector}_j \times \text{I}(2011 \leq \text{Year} \leq 2012) + \\ & \beta_2 \text{ETS}_r \times \text{Sector}_j \times \text{I}(\text{Year} \geq 2013) \times \text{Price}_{rt} + \gamma' X_{it} + \lambda_i + \delta_{jt} + \eta_{rt} + \varepsilon_{ijrt} . \end{aligned} \tag{5}$$

The model distinguishes the ETS effect in two periods. During 2011 and 2012, carbon market pilots were announced and the regulated firms started to manage their carbon emissions, which is measured by the first item on the right-hand side of equation Eq (5). After 2013, the trading of carbon allowances started and carbon price provides essential information for firms to make decisions on compliance. The effect of ETS in the second period is measured by the second item in the above equation. Similarly, we can combine Eqs (2) and (5) to analyze the effect in two periods for the regulatory exposure specification.

4 Data and Variables

4.1 Data Sources

We have assembled a comprehensive dataset of economic and innovation activities for 2,142 Chinese listed firms and their subsidiaries between 2003 and 2016. The data pertain to the listed firms in the manufacturing and utility sectors, integrating detailed firm-level information about patents granted in all technological fields, R&D expenditures, and economic fundamentals. We compile the data from three sources. The China Stock Market and Accounting Research (CSMAR) Solution provides the firm-level economic fundamentals and corporate tree structures including a list of subsidiary firms and their shareholdings.[11] The State Intellectual Property Office (SIPO) of China supplies detailed patent information including application number, application date, grant number, grant date, and main International Patent Classification (IPC) code.[12] The National Enterprise Credit Information Publicity System at the State Administration for Industry and Commerce of China reports city location and industry information for subsidiaries associated with listed firms. We match and merge Chinese listed firms and subsidiaries with those that have filed patent applications based on the SIPO archives.

We further obtain carbon prices from the seven pilot carbon markets. Allowance trading started in Shenzhen in Q3 2013; Guangdong, Shanghai, Beijing, and Tianjin started trading in Q4 2013; and Chongqing and Hubei started trading in Q2 2014. Therefore, the carbon price is available between Q3 2013 and Q4 2016, the end of our sample period. Figure A1 plots quarterly carbon prices across regional pilots.

In the end, our data contain 21,531 firm-year observations associated with 2,142 unique listed firms and 57,842 subsidiaries. During the study period, there are around 0.9 million patent applications that have been successfully granted, and roughly less than 8 percent of patents are related to low-carbon technologies. Among all granted patents, 0.4 million patents are applied by parent firms, while the remaining patents are applied by subsidiaries.

[11]The CSMAR performs a similar role as the Compustat database access from Wharton Research Data Services.

[12]In 1980, China founded its patent office, the SIPO, and adopted a patent system similar to those used in Europe and Japan. Since August 28th of 2019, the SIPO of China has been renamed to China National Intellectual Property Administration.

4.2 Variable Construction

The primary dependent variable is concerned with firm patenting. China grants three types of patents: invention patents, utility model patents, and design patents. Invention patents and utility model patents, whose IPC codes are in line with the definition of the World Intellectual Property Organization (WIPO), are most relevant to low-carbon innovation.[13] The invention patents represent practical, inventive, and new technical innovations, which are substantively examined by SIPO. The utility model patents, or the so-called minor patents in China, are associated with technical solutions to the shape or structure of an object, which are only subject to formality examinations. Therefore, invention patents represent the most important innovations in China's patent system (Liu and Qiu, 2016; Hu, Zhang, and Zhao, 2017; Wei, Xie, and Zhang, 2017).

To classify low-carbon technologies, we match each granted patent's main IPC code with the IPC Green Inventory code, which is developed by WIPO's IPC Committee of Experts. The IPC Green Inventory classifies environmentally sound technologies based on the list provided by the United Nations Framework Convention on Climate Change (UNFCCC).[14] We define low-carbon innovation as the technologies associated with alternative energy production, energy conservation, and waste management. We also conduct robustness checks by narrowing down the definition to only alternative energy production and energy conservation.

We use the share of low-carbon patents as an indicator for firm innovation. It measures whether regional ETS pilots induce the direction of technological changes towards low-

[13] The design patents, targeted to the external appearance of products and not related to low-carbon functionality or inner workings, are excluded from our analysis

[14] The European Patent Office (EPO) has recently developed a new category of IPC codes, dubbed as the Y02 class, pertaining to technologies or applications for mitigation or adaptation against climate change (Haščič and Migotto, 2015; Calel and Dechezleprêtre, 2016). This list of low-carbon technologies includes, for example, efficient combustion technologies, carbon capture and storage, efficient electricity distribution, and alternative energy production. Although China SIPO does not have adopted the Y02 class yet, we have cross-checked the sub-class of this Y02 class with the IPC Green Inventory and find some similarities between these two classifications of low-carbon technologies. Our results are robust to this alternative definition of low-carbon technologies

carbon technologies. We use shares instead of counts to mitigate the concern that both climate-friendly innovation and other innovative activities are subject to the same policy shocks (Popp, 2002). To differentiate the quality of innovation, we also use the shares of invention and utility model patents in all climate-related patents. The share of low-carbon invention patents is employed as a primary dependent variable for high-quality innovation activities. As a robustness check, we also run the same regression using the counts of low-carbon patents.

Another important dependent variable is concerned with firms' financial performance, which is measured by return on assets (ROA), return on equity (ROE), and return on capital employed (ROCE). ROA, which is defined by the ratio of net income to total assets, focuses on the financial efficiency of assets. ROE, which is calculated by dividing net income by average shareholder's equity, focuses on the return on net assets. ROCE, which is calculated by dividing the earnings before interest and tax to total capital employed, focuses on the utilization efficiency of a firm's available capital. The three indicators are widely used to evaluate listed firms' profitability.

The central explanatory variable is ETS. The seven regional pilots cover a range of carbon-intensive manufacturing and public utility sectors, including power and heating, chemical, iron and steel, and cement. We define the covered sectors as those carbon-intensive manufacturing and public utilities that appeared in any pilot regions. We then correspond the covered sectors with the two-digit industry codes. Table A2 in the Online Appendix provides a summary of the covered sectors and the standard industrial classifications. In the robustness check, we narrow down the classification of covered sectors to those carbon-intensive sectors chosen by the majority of regional ETS pilots.

Table 1 reports the summary statistics for the variables used in the empirical analysis, including several measures of low-carbon innovation, financial performance measures, firms' characteristics relevant to competitiveness, and regional carbon prices.

[Insert Table 1 about here]

5 Empirical Results

In this section, we report the empirical results for the estimated effect of regional ETS pilots on firm innovation. We also present a set of robustness analyses to check the sensitivity of model specifications and assumptions. Furthermore, we disentangle the ETS effect by different phases, focusing on how carbon price affects firms' incentives for low-carbon innovation. Along this line, we present some additional effects on innovation. Lastly, but not least, we explore how the firm's financial performance responds to the ETS and whether the adjustments are related to low-carbon innovation.

5.1 Analysis of Sample Means

Before running regressions, we conduct a sample mean analysis to compare low-carbon patenting for the regulated and unregulated sectors. The results are summarized in Table 2. We start from columns (1)-(3), the result for the share of low-carbon patents in all patents. Panel A is the DD estimate of interest, in which we compare the shares of low-carbon patents between the covered sectors in the pilots and the same sectors in the non-pilots, before and after ETS. The DD estimate suggests that ETS increases the share of low-carbon patents by 0.013 percentage points, significant at the 95 percent level. Panel B is a placebo DD estimate since the non-covered sectors are not regulated in either pilot regions or non-pilot regions at all. As expected, the placebo DD estimate is statistically insignificant from zero, suggesting that the DDD identification assumption is likely valid.

[Insert Table 2 about here]

The DDD estimate is simply the difference between the DD estimate of interest and the placebo DD estimate. We find that the sectors subject to the ETS policy increase the share of low-carbon patents by 0.016 percentage points. This statistically significant DDD estimate suggests that the regional ETS pilots direct sectoral innovation activities towards climate-friendly technologies. Furthermore, we conduct a similar analysis for the invention patents, and the results are shown in columns (4)-(6) in Table 2. The conclusion is similar to the previous analysis.

5.2 Baseline Regression Results

We estimate the baseline model in Eq 1 using the firm-level data. The results are presented in Panel A of Table 3. The regression framework allows us to control for observable time-varying firm attributes, as well as a set of fixed effects at the firm, industry-by-year, and province-by-year levels.[15] In all regressions, standard errors are clustered at the sector level. In column (1), we report the results for the share of low-carbon patents in all patents. The estimate is positive and statistically significant at the 5 percent level, suggesting that ETS increases the share of low-carbon patents by 0.021 percentage points. For the level of low-carbon patents, similar findings are documented in Table A4. It suggests that ETS increases low-carbon patent counts by 20.5 percent.

[Insert Table 3 about here]

Not all patents are created equal. We are concerned about the quality of innovation by differentiating invention and utility model patents. The invention patents represent practical, inventive, and new technical innovations, while the utility model patents refer to technical solutions to the shape or structure of an object. Columns (2) and (3) of Table 3 separates the DDD estimate in column (1) by patent types. Both estimates are positive, but only the estimate for the invention patents is statistically significant at the 5 percent level. It suggests that ETS stimulates more high-quality innovation embodied by invention patents instead of marginal innovation represented by utility model patents.

Among the invention patents, we further seek to identify whether ETS directs innovation towards low-carbon technologies. In column (4), we focus on the share of low-carbon patents in invention patents. The result shows that ETS increases the share of low-carbon

[15] The inclusion of the fixed effects and firm attributes one by one does not alter the main conclusion. The results are presented in Table A3 in Appendix.

patents in invention patents by 0.029 percentage points, statistically significant at the 1 percent level. The effect is of great economic significance, which is equivalent to a 97 percent growth in low-carbon patents. The result suggests that ETS has created stronger incentives toward more substantive innovation.

Considering that a listed firm may have subsidiaries spreading over different regions and sectors, we also run regressions to estimate the alternative model in Eq (2). We measure the listed firm's exposure to ETS using the formula defined in Eq (3). The results are shown in Panel B of Table 3. The conclusion is similar to the analysis in Panel A in terms of the magnitude and significance of coefficient estimates. It suggests that as more subsidiaries from a listed firm are covered under ETS, the stronger the ETS policy-inducing innovation effect would be.

The major identification assumption is that the patenting trends for the regulated and unregulated firms evolve in parallel before the policy intervention. To check the validity of this assumption, we conduct the following parallel trends test by running a variant of the DDD model while controlling for the lags and leads of the policy year dummies:

$$\begin{aligned} Y_{ijrt} =& \beta_0 + \sum_{m=1}^{7} \beta_{1m} \mathrm{ETS}_r \times \mathrm{Sector}_j \times \mathrm{Post}_{t-m} + \\ & \sum_{n=1}^{5} \beta_{2n} \mathrm{ETS}_r \times \mathrm{Sector}_j \times \mathrm{Post}_{t+n} + \gamma' X_{it} + \lambda_i + \delta_{jt} + \eta_{rt} + \varepsilon_{ijrt}. \end{aligned} \tag{6}$$

In this form, Setor_j is one if sector j is covered and zero otherwise; ETS_r is one if region r is an ETS pilot and zero otherwise; Post_{t-m} is a pre-policy dummy indicating the m^{th} lag of ETS announcement year, while Post_{t+n} denotes a post-policy indicator for the n^{th} lead. Controlling for lags allows us to examine the pre-ETS effect as a placebo test and helps isolate the anticipation effect from the actual policy effect. Controlling for the leads helps trace out the treatment effect in the years after the launching of regional ETS pilots.

[Insert Figure 1 about here]

Figure 1 illustrates the estimated coefficients and 95 percent confidence intervals. The upper panel plots the dynamic effect for the share of low-carbon patents. The estimated coefficients for the pre-policy indicators are not statistically significant at any conventional level. These findings provide evidence in support of the parallel trends assumption that the low-carbon patenting was not statistically different between the regulated and non-regulated firms before ETS. After the announcement of ETS in 2011, the estimated coefficients for the post-policy indicators become statistically significant, and their magnitudes increase. The induced innovation effect of ETS starts to phase in and displays an upward trend. After 2014, the ETS effect then gradually phases out and eventually vanishes in 2016. The lower panel plots the dynamic effect for the share of low-carbon invention patents, which follows a similar pattern.

In addition to the share of low-carbon patents, we also examine the ETS effect on patent counts. Table A4 in the Online Appendix presents the corresponding results varying by fixed effects. For the preferred specification in column (5), ETS contributes to a 0.205 percentage point increase in all low-carbon patents and a 0.142 percentage point increase in invention patents. Figure A2 in the Online Appendix illustrates the estimated dynamic effect for patent counts. We found no evidence that the trends of low-carbon patenting are different for the regulated and unregulated firms in the pre-ETS period. The post-ETS dynamics are also similar to those in the main results.

5.3 Robustness

To test the stability of main conclusions, we have conducted a series of robustness checks regarding potential confounders, alternative model specifications, and alternative identification strategies. The results are summarized in Table 4. Overall, the main conclusions survived all these robustness checks.

[Insert Table 4 about here]

We test the sensitivity of our results regarding potential confounding environmental, energy, and innovation policies. To deal with regional air pollution control policies that target Beijing, Tianjin, and Hebei (BTH), which overlap with the regional ETS pilots, we drop the samples from BTH (row *a*). To test the potential impact of the nationwide energy policy devoted to subsidizing the innovation and adoption of PV, we remove the patents associated with PV technologies (row *b*). To test the potential impact of the nationwide tax incentives for innovation,[16] which reduces the tax rate for the firms with a high-tech status from 25 percent down to only 15 percent, we drop the observations for a list of certified high-tech firms according to CSMAR (row *c*). None of these tests change the main conclusions.

We test several alternative assumptions and model specifications. Considering that innovation takes time, we use two-year forward patents as an alternative outcome variable (row *d*). We narrow down the definition of low-carbon patents to those related to alternative energy production and energy conservation, in line with the EPO classification of low-carbon technologies under the new category of the Y02 class (row *e*). We use two alternative approaches to consistently estimate the standard errors: one approach (row *f*) is to collapse the data into two periods and re-run the regression of the baseline model (Bertrand, Duflo, and Mullainathan, 2004)[17] and the other approach (row *g*) is to cluster standard errors at the industry-province level. Relevantly, we also control for province-industry fixed effect (row *h*). Considering the fact that each ETS pilot covers a different set of sectors, we narrow down the treatment group to electricity, heating, steel and iron, cement, and petrochemical industries, which are the most carbon-intensive industries regulated by more than five ETS pilots (row *i*). We measure listed firms' exposure to ETS by the weighted average of all its subsidiaries' exposure defined in equation (3) (row *j*). The estimated effects of ETS on low-carbon patenting are still robust.

[16] It covers the certified high-tech firms in renewable energy, energy conservation, resources and environmental technologies, new materials, electronics engineering, and others.

[17] Specifically, we collapse the 2003-2016 period into two periods: one is before the announcement year of 2011, and the other is after.

We also employ alternative strategies to identify the effect of ETS on low-carbon patenting. We adopt the DD approach to estimate the baseline model, which assumes away sectoral or regional restrictions imposed on the control groups. The corresponding results are reported in row k. In addition, we match the regulated firms with unregulated ones,[18] combining PSM with the nearest neighbor matching estimator. That is, for the regulated firms we select similar unregulated firms conditional on their observable characteristics.[19] With this restricted matched sample, we adopt a variant of the DD approach to examine the effect of ETS on low-carbon patenting. The results are close to our baseline estimates.

In addition to the above robustness checks, we also implement a placebo test to rule out the possibility that low-carbon innovation is driven by factors other than ETS. We consider the water pollution-intensive sector as the pseudo-covered sector while assuming water pollution-related patents as the dependent variable of interest. We probe the robustness of our results by estimating the effect of ETS on water pollutants-related innovation, which should be zero since the water pollution-intensive sector is not the target of regional ETS pilots. We use two binary indicators to indicate water pollution-intensive sectors: one is taken from Cai, Chen, and Gong (2016) and the other is obtained from the census of Pollution Statistics Survey in China Census Statistics. The placebo test results are presented in Table A6 in the Online Appendix. As expected, we find no statistically significant effect of ETS on patenting not related to climate technologies. It suggests that

[18] A firm with at least one regulated parent or subsidiary is regarded as an ETS regulated firm.

[19] The propensity score of each firm is calculated based on their pre-ETS financial and innovation indicators, including total assets, capital, and revenue in the two years before the firm was enrolled into an ETS pilot, and accumulative levels of total and low-carbon patenting activities by one year before the ETS. There is a lack of consensus on which variables should be included when calculating propensity scores. A large number of restrictions and variables, while deemed stringent and safe, tend to cause fewer matched pairs. Therefore, we choose the variables that are strongly correlated with outcome, avoid losing too many matched pairs while ensuring balance. All covariates are log-transformed. Replacement is allowed in the matching procedure so that an unregulated firm could be matched for multiple regulated firms. Matching quality is evaluated by comparing the sample means of the outcome and variables used in the matching procedure between the treatment group and the control group. Online Appendix Table A5 provides the balancing test. In the unmatched sample, as shown in columns (1)-(3), substantial differences in the observed characteristics are documented between the treated and control groups. In the matched sample, there exist little statistically significant differences between the two groups in the pre-ETS period. These observations suggest that the matching procedure performs well in obtaining control units that are comparable to regulated firms.

the carbon-reducing innovation is driven by ETS rather than other environmental policies.

5.4 Allowance Trading and Price

The seven regional ETS pilots are implemented in two phases. In Phase I (2011 – 2012), the regional ETS pilots were officially announced. In Phase II (2013-2016), carbon allowance trading started, sending price signals to the regulated firms. We disentangle the ETS effect by these two phases using a variant of the baseline model in Eq (5),

Panel A of Table 5 reports the estimation results. In columns (1) and (3), the coefficient estimates for the triple interaction terms in both periods are positive and statistically significant. The magnitudes of Phase II estimates are greater than those in Phase I, suggesting the importance of allowance trading and price in stimulating innovation. In columns (2) and (4), we further interact the triple interaction term with the carbon price, and the estimates are positive and statistically significant at the 1 percent level. It suggests that a higher carbon price sends a stronger signal for stimulating low-carbon patenting.

[Insert Table 5 about here]

Accounting for listed firms' exposure to ETS defined in Eq (4), we decompose the effects of ETS on listed firms by two phases. Panel B of Table 5 reports the results. Findings are similar to those in Panel A. In columns (1) and (3), the coefficient estimates for ETS exposure in Phase I are positive and significant, but their magnitudes are smaller than those in Phase II. In columns (2) and (4), the estimates confirm that higher carbon prices create more incentives for innovation. Overall, accounting subsidiaries' exposure to ETS does not alter our main conclusions.

5.5 Innovation Quality and Crowding-out

The existing literature measures the innovation quality using patent count weighted by the number of future citations received (Hall, Jaffe, and Trajtenberg, 2005; Calel and

Dechezleprêtre, 2016).[20] To this end, we retrieve future patent citations associated with all low-carbon patent applications from the Google Patent Project from 2010 to 2017.[21] Using the low-carbon innovation quality as an alternative measure, columns (1) and (2) in Table 6 provide the corresponding results. Panel A separates the ETS effect into two phases, Panel B incorporates the carbon price of Phase II, and Panel C considers listed firms' exposure to ETS. Similar to the baseline results, these estimates highlight the ETS effect mainly occur in Phase II: allowance trading and price play a substantial role in improving the quality of low-carbon patenting.

[Insert Table 6 about here]

We also explore the ETS effect on innovation quality by patent types. Specifically, we compare the effects for invention and utility model patents. Columns (3) and (4) of Table 6 report the corresponding coefficient estimates. For the high-quality invention patents, the ETS has no effects in Phase I but has a significantly positive effect in Phase II. It suggests that carbon price provides the most important incentive in directing innovation towards more high-quality low-carbon technologies. The result is ambiguous for the low-quality utility model patents.

There is a concern that ETS may crowd out the innovation of technologies not related to climate change (Calel and Dechezleprêtre, 2016; Zhu et al., 2019). To test this, we estimate the ETS effect on the patents other than carbon-reducing technologies. Table A7 in the Online Appendix shows the results for water pollution patents. Panel A follows the baseline DDD model, Panel B separates into two phases with the carbon price, and Panel C considers listed firms' exposure to ETS. All estimated coefficients in all panels are positive, but most are not statistically significant at the conventional level. Overall, these findings suggest that the crowding-out effect of ETS on water pollution-related innovation

[20] The literature also suggests use patent family size as an alternative measure for patent quality. However, we do not obtain relevant information.

[21] Unlike the USPTO or EPO, patent examiners at the SIPO of China do not have mandatory requirements for adding citations when filing patent applications. Hence a few citations are documented before 2010.

is muted.

5.6 Firm Financial Performance

It is at the center of policy debate whether and how ETS affects firm financial performance. The existing literature has examined the effects of ETS in the United States (for example NO_x Budget Program) on firm profits (Linn, 2010), investment in pollution abatement (Fowlie, 2010), emission abatement (Fowlie, Holland, and Mansur, 2012), and labor employment (Curtis, 2017). As for the EU ETS, a plethora of conflicting empirical evidence regarding the financial impact of the EU ETS has emerged (Veith, Werner, and Zimmermann, 2009; Commins et al., 2011; Bushnell, Chong, and Mansur, 2013; Marin, Marino, and Pellegrin, 2018).[22]

Based on the baseline model (1), we estimate the ETS impacts on firms' market value and other attributes. Table 7 shows the corresponding results. Columns (1)-(3) report the estimates for ROA, ROE, and ROCE. The estimates suggest that the ETS has statistically insignificant effects on firms' ROA and ROE. The estimate is positive, statistically significant at the 5 percent level for ROCE. To summarize, the bottom line is that there is no evidence that carbon ETS harms firm profitability.

[Insert Table 7 about here]

Along this line, we examine if ETS affects other firm attributes such as asset, liability, intangible asset, revenue, cost, profit, and R&D expenditure. Columns (4)-(10) of Table 7

[22] Commins et al. (2011) examine the economic impacts of the EU ETS in the first phase. They find some negative effects on firms' TFP and ROCE but no significant impact on employment and investment. Along this line, Marin, Marino, and Pellegrin (2018) provide a comprehensive assessment of the first and second phases of the EU ETS on firms' economic performance over the 2005-2007 and 2008-2012 periods. Due to the passing-through effect of regulatory costs to customers, their findings suggest little evidence regarding the negative impacts of the ETS on firms' economic and financial indicators. As carbon price captures the stringency of the ETS, both Veith, Werner, and Zimmermann (2009) and Bushnell, Chong, and Mansur (2013) further document the positive correlation between the carbon price in the EU ETS and stock returns of firms in power sectors due to the pass-through effect from regulatory costs to their customers. The former focuses on both spot and future carbon prices, while the latter exploits a sharp and sudden drop in the EU carbon allowance price in late April 2006.

present the estimation results. All estimates are statistically insignificant, suggesting that ETS has no effects on these firm attributes. The result for R&D expenditure should be interpreted with caution because of the severe missing data problem. It is worth noting that these findings can also provide corroborating support to the balancing sample across the covered sectors, pilots, and ETS periods along with a set of firm-level dimensions.

We conjecture that an early mover in low-carbon innovation has an advantage in achieving better financial performance under ETS. To test this hypothesis, we run new regressions that include the knowledge stock of low-carbon patents accumulated before the ETS. We first take the two-year observations before and after 2011. We then collapse the data into two periods and calculate the average of firm-level variables, including profitability indicators, covariates, and the stock of low-carbon patents. As robustness checks, we also use one-year and three-year observations before and after 2011. Let Stock_i denote the stock of low-carbon patents accumulated before 2011. We regress firm financial performance R_{ijrt} on the interaction term among the region, time, and low-carbon patent stock as well as other covariates and fixed effects:

$$R_{ijrt} = \beta_0 + \beta_1 \text{Sector}_j \times \text{Post}_t \times \text{Stock}_i + \gamma' X_{it} + \lambda_i + \delta_{jt} + \eta_{rt} + \varepsilon_{ijrt}. \tag{7}$$

The above regression is run on the split samples for the ETS and non-ETS regions. The estimation results are reported in Table 8. In the ETS regions, we find that low-carbon patent stocks accumulated before 2011 have non-negative impacts on ROA, ROE, and ROCE for the covered sectors after 2011; however, the effects are statistically insignificant for the non-ETS regions. This result suggests that ETS stimulates innovation, which in turn reduces the cost of compliance with ETS.

[Insert Table 8 about here]

5.7 Discussion

Technological innovation is the ultimate solution to the climate change problem. As the world's largest GHG emitter, China's climate ambition hinges on whether climate policy can spur low-carbon innovation, which reduces the cost of compliance with its climate commitments. Our analysis demonstrates unambiguous evidence that ETS stimulates low-carbon patenting. Costantini et al. (2017) find that the correlation between the stock of eco-innovation and carbon emission intensity is around -0.081. We estimate that China's regional ETS pilots increase by around 20.5 percent low-carbon patents. A back-of-the-envelope calculation suggests ETS can lead to a 1.66 percent decrease in carbon intensity. The average carbon price in China was 28 Yuan/ t-CO_2 during 2013-2016. If China increases the carbon price to the same level as California ($15/ton), it will increase low-carbon patents by 21.85 percent, leading to a 1.77 percent decline in carbon intensity. If carbon price is set at the level of the social cost of carbon ($50/ton) (Nordhaus, 2019), it will further increase low-carbon patenting by 91.72 percent and hence give rise to a reduction in emission intensity by 7.43 percent.[23]

Our results also shed light on the just-launched national carbon ETS in China. The national ETS, still adopting the rate-based TPS, will cover around 3,500 MT CO_2. We predict that the national ETS will increase China's low-carbon patenting by around 5.46 percent.[24] Although China's national ETS only covers the power sector in the first stage, it

[23]Our estimate of the carbon price elasticity of low-carbon patent count is 0.085. The policy effects assumed in different carbon price scenarios are calculated as follows. The price elasticity of low-carbon innovation is 0.085. When the carbon price rises to $15 (amounts to 100 yuan and the price change is around 257 percent), it will increase low-carbon patents by $0.085 \times 257\% = 21.85\%$ and decrease the intensity by $21.85\% \times 0.081 = 1.77\%$. When the price rises to $50 (around 330 yuan and price change is 1079 percent), low-carbon patents increase by $0.085 \times 1079\% = 91.72\%$ and the intensity decreases by $91.72\% \times 0.081 = 7.43\%$.

[24]Here we assume the case if all firms in covered sectors but not regulated by ETS pilots are finally enrolled into the national ETS. The national ETS effect is calculated in the following steps: in our sample, we have 132 ETS firms and 2,014 Non-ETS firms. Among 2,014 Non-ETS firms, 440 firms are in regulated sectors while 1,574 are not. If assuming that the samples could stand for the distribution of Chinese firms (middle and large size), the national ETS then covers the 440 firms, and the ratio of regulated firms would become $(132 + 440)/(132 + 2014) = 26.65\%$. If assuming no other factors and control units that affect low-carbon innovation, the induced-innovation effect on overall Chinese firm-level low-carbon innovation is $20.5\% \times 26.65\% = 5.46\%$. If focusing on the single electricity industry, due to only 40 Non-ETS firms in this industry, the increase rate is around 1.64 percent.

will still overtake the EU ETS to become the world's largest carbon market. With expanding the covered sectors, the national ETS would become a central policy instrument to achieve China's climate target. The experience from regional ETS pilots shows that even a relatively low carbon price can induce innovation, as long as the covered firms are cognizant of the fact that ETS will be implemented and maintained in the long term.

6 Conclusion

In this paper, we assess the economic impacts of China's carbon ETS pilots on firm low-carbon innovation and financial performance. Using patent data on Chinese publicly listed firms and their subsidiaries, we compare low-carbon patenting for the regulated and regulated firms. We find consistent and robust evidence supporting the directed technical change induced by ETS, which contributes to a 0.021 percentage points increase in the share of low-carbon patents and a 20.5 percent increase in the total number of low-carbon patents. Using carbon price as a signal of regulatory stringency across jurisdictions, we show that a higher carbon price creates more incentives for low-carbon patenting and leads to an increase in the innovation quality measured by patent citations. Lastly, there is no evidence that carbon ETS harms firm profitability.

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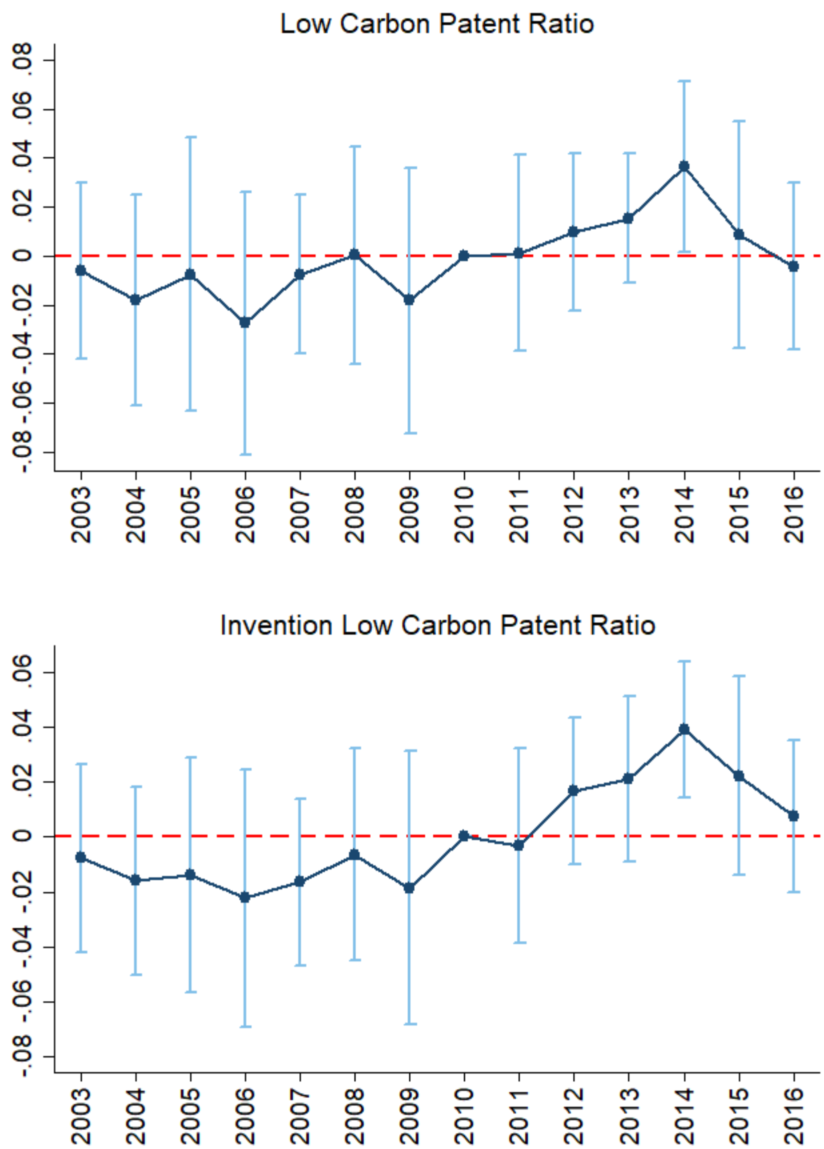

Figure 1: Dynamic Effect for Low-carbon Patent Ratio
Note: Charts from up to down show the dynamic impacts of ETS on the share of low-carbon patent in all patents and the share of low-carbon patent in invention patents. Blue dots represent estimated coefficients of time-specific indicators, while vertical lines indicate the 95% confidence intervals. A variant of the baseline DDD regression specification (6) is conducted for firms' innovation outcomes.

Table 1: Summary Statistics

VARIABLES	N	Mean	Std. Dev.		
			overall	betweeen	within
	(1)	(2)	(3)	(4)	(5)
Panel A. Patent Information					
Total patent	26,111	27.50	185.79	129.72	141.24
Total invention patent	26,111	13.24	103.43	63.43	83.01
Low carbon patent	26,111	1.67	12.36	7.27	10.04
Low carbon invention patent	26,111	0.83	7.94	4.13	6.74
Share of low-carbon patents in all patents	26,111	0.03	0.09	0.06	0.08
Share of low-carbon patents in invention patents	26,111	0.03	0.09	0.05	0.08
Panel B. Firm Attributes					
Return on Assets (ROA)	22,604	1.01	157.11	36.33	151.42
Return on Equity (ROE)	22,604	0.07	5.32	1.24	5.12
Return on Capital Employed (ROCE)	22,271	0.11	5.16	1.28	4.95
Firm age	26,111	14.43	5.52	4.17	3.67
Total assets	22,604	21.68	1.29	1.06	0.67
Total capital	22,246	21.03	1.22	0.99	0.68
Intangible assets	21,811	18.10	1.89	1.46	1.24
Operating revenue	22,591	21.04	1.55	1.32	0.74
Panel C. Carbon Market					
Carbon price	26,111	3.28	11.28	6.13	9.72

Notes: Between/within standard deviation captures the variation between/within each listed firm.

Table 2: The DDD Estimate of the ETS Effect Using Sample Means

	Share of Low-carbon Patents in All Patents			Share of Low-carbon Patents in Invention Patents		
	Before (1)	After (2)	Differences (3) = (2) - (1)	Before (4)	After (5)	Differences (6) = (5) - (4)
Panel A. Covered Sectors						
ETS regions	0.022	0.063	0.041***	0.019	0.056	0.037***
	(0.092)	(0.134)	(0.005)	(0.082)	(0.134)	(0.005)
Non-ETS regions	0.018	0.046	0.028***	0.015	0.040	0.025***
	(0.080)	(0.105)	(0.003)	(0.073)	(0.104)	(0.002)
ETS - Non-ETS	0.004	0.017***	0.013**	0.004	0.016***	0.012**
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
Panel B. Non-covered Sectors						
ETS regions	0.017	0.040	0.023***	0.015	0.037	0.022***
	(0.074)	(0.108)	(0.002)	(0.071)	(0.109)	(0.002)
Non-ETS regions	0.014	0.040	0.026***	0.010	0.036	0.026***
	(0.070)	(0.104)	(0.002)	(0.061)	(0.107)	(0.002)
ETS - Non-ETS	0.003	0.000	-0.003	0.005**	0.001	-0.004
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
DDD			**0.016*****			**0.016*****
			(0.006)			(0.006)

Notes: The numbers are mean values of samples by pre- and post-ETS periods, ETS and non-ETS regions, and covered and non-covered sectors. Column (3) is the mean difference between columns (1) and (2), while column (6) is the mean difference between columns (4) and (5). Standard errors are presented in the parenthesis. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 3: Baseline Results of the Effects of Carbon ETS

DEPENDENT VARIABLES	Share of Low-carbon Patents in All Patents (1)	Share of Low-carbon Invention Patents in All Patents (2)	Share of Low-carbon Utility Patents in All Patents (3)	Share of Low-carbon Patents in Invention Patents (4)
Panel A. Baseline Specification				
ETS×Sector×Post	0.021**	0.012**	0.009	0.029***
	(0.011)	(0.005)	(0.006)	(0.010)
Panel B. Listed Firms' Exposure to ETS (Unweighted)				
Exposure	0.030***	0.013***	0.017**	0.023***
	(0.011)	(0.005)	(0.008)	(0.010)
Observations	21,531	21,531	21,531	21,531
Firm Attributes	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y

Notes: Panel A refers to the baseline DDD model Eq (1), Panel B refers to the listed firms' exposure model Eq (2). ETS is a dummy for regional ETS pilots, Sector is a binary indicator for the covered sectors, and Post is a dummy for year 2011 and after. Exposure is the alternative measures of policy treatment accounting for parent company's exposure to ETS as the average of all its subsidiaries' exposures. Firm attribute includes firm age, asset, capital, revenue, operating cost, and knowledge stock. A set of fixed effects at firm, province-year, and industry-year is included. Standard errors presented in the parenthesis are clustered at industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 4: Robustness Check: Confounding Factors and Alternative Model Specifications

DEPENDENT VARIABLES	Share of Low-carbon Patents in All Patents (1)	Share of Low-carbon Invention Patents in All Patents (2)	Share of Low-carbon Utility Patents in All Patents (3)	Share of Low-carbon Patents in Invention Patents (4)
a. Drop samples from the BTH area	0.024**	0.014**	0.010	0.028***
	(0.012)	(0.006)	(0.007)	(0.010)
b. Drop PV patents	0.019**	0.010**	0.008	0.027***
	(0.009)	(0.005)	(0.006)	(0.009)
c. Drop high-tech firms	0.042**	0.021**	0.021**	0.045***
	(0.016)	(0.008)	(0.010)	(0.014)
d. Lagged effects (two-year forward)	0.023*	0.014*	0.009	0.026*
	(0.013)	(0.007)	(0.008)	(0.013)
e. Narrowed definition of low-carbon tech	0.016**	0.011**	0.006	0.022***
	(0.008)	(0.004)	(0.006)	(0.008)
f. Two-period DD	0.017*	0.009**	0.008	0.022**
	(0.010)	(0.005)	(0.007)	(0.009)
g. Province-industry clustered std errors	0.021**	0.012**	0.009	0.029***
	(0.010)	(0.006)	(0.006)	(0.009)
h. Additional control for province-industry FE	0.021**	0.012**	0.009	0.029***
	(0.010)	(0.005)	(0.006)	(0.010)
i. Alternative covered sectors	0.028*	0.021***	0.008	0.047***
	(0.016)	(0.007)	(0.011)	(0.016)
j. Listed Firms' exposure (weighted)	0.043***	0.020***	0.023**	0.033**
	(0.015)	(0.007)	(0.010)	(0.013)
k. Naive DD model	0.021**	0.013***	0.009	0.030***
	(0.009)	(0.005)	(0.006)	(0.009)
l. PSM (nearest neighbor matching)	0.027*	0.016***	0.011	0.028***
	(0.015)	(0.005)	(0.014)	(0.009)

Notes: Rows *a* to *i* refer to the baseline DDD model Eq (1), Row *j* is the listed firms' exposure model Eq (2) accounting for subsidiaries' shareholdings as weight. Row *k* is a naive DD model, and Row *l* is the PSM model. Firm attribute includes firm age, asset, capital, revenue, operating cost, and knowledge stock. A set of fixed effects at firm, province-year, and industry-year are included. Standard errors presented in the parenthesis are clustered at industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 5: Mechanism: Disentangle the Startup Effect and the Trading Effect

DEPENDENT VARIABLES	Share of Low-carbon Patents in All Patents		Share of Low-carbon Patents in Invention Patents	
	(1)	(2)	(3)	(4)
Panel A. Baseline DDD and Market Intensity Model				
ETS$\times$ Sector$\times I(2011 \leq \text{Year} \leq 2012)$	0.015*	0.019**	0.019**	0.020**
	(0.008)	(0.008)	(0.008)	(0.009)
ETS$\times$ Sector$\times I(\text{Year} \geq 2013)$	0.024**		0.034***	
	(0.011)		(0.012)	
ETS$\times$ Sector$\times I(\text{Year} \geq 2013)\times$Price		0.010***		0.011***
		(0.003)		(0.003)
R-squared	0.093	0.093	0.094	0.095
Panel B. Listed Firms' Exposure Model				
Exposure$\times I(2011 \leq \text{Year} \leq 2012)$	0.020**	0.016*	0.015*	0.011
	(0.009)	(0.008)	(0.009)	(0.009)
Exposure$\times I(\text{Year} \geq 2013)$	0.036**		0.027**	
	(0.014)		(0.012)	
Exposure$\times I(\text{Year} \geq 2013)\times$Price		0.010**		0.007*
		(0.004)		(0.004)
R-squared	0.093	0.093	0.094	0.094
Observations	21,531	21,531	21,531	21,531
Firm Attributes	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y

Notes: Panel A refers to the carbon market model Eq (5). Panel B refers to the listed firms' exposure model Eq (2) while accounting for carbon market performance. Price denotes carbon price for regional ETS pilots. Firm attribute includes firm age, asset, capital, revenue, operating cost, and knowledge stock. A set of fixed effects at firm, province-year, and industry-year is included. Standard errors presented in the parenthesis are clustered at industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 6: Extension: The Effect of ETS on the Quality of Innovation

DEPENDENT VARIABLES	All Patents weighted by Citations (1)	Invention Patents weighted by Citations (2)	Share of Invention Low-carbon Patents in All Patents (3)	Share of Utility Low-carbon Patents in All Patents (4)
Panel A. Baseline DDD model				
ETS×Sector×I(2011 ≤ Year ≤ 2012)	0.116	0.047	0.002	0.013*
	(0.122)	(0.090)	(0.005)	(0.007)
ETS×Sector×I(Year ≥ 2013)	0.198	0.142	0.017***	0.007
	(0.133)	(0.100)	(0.006)	(0.007)
R-squared	0.249	0.199	0.084	0.086
Panel B. Carbon Market Model				
ETS×Sector×I(2011 ≤ Year ≤ 2012)	0.135	0.062	0.004	0.015**
	(0.114)	(0.082)	(0.005)	(0.007)
ETS×Sector×I(Year ≥ 2013)×Price	0.072**	0.052*	0.006***	0.004
	(0.036)	(0.028)	(0.002)	(0.002)
R-squared	0.249	0.199	0.084	0.086
Panel C. Listed Firms' Exposure to ETS and Carbon Price				
Exposure×I(2011 ≤ Year ≤ 2012)	0.013	-0.001	0.006	0.010
	(0.093)	(0.075)	(0.004)	(0.006)
Exposure×I(Year ≥ 2013)×Price	0.041*	0.032*	0.004**	0.006**
	(0.024)	(0.018)	(0.002)	(0.003)
R-squared	0.260	0.211	0.083	0.087
Observations	21,531	21,531	21,531	21,531
Firm Attributes	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y

Note: Panels A and B denote the carbon market model Eq (5), and Panel C is the listed firms' exposure model Eq (2) while accounting for carbon market performance. Firm attribute includes firm age, asset, capital, revenue, operating cost, and knowledge stock. A set of fixed effects at firm, province-year, and industry-year is included. Standard errors presented in the parenthesis are clustered at industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 7: Extension: The ETS Effects on Firm Financial Performance and Other Attributes

DEPENDENT VARIABLES	ROA (1)	ROE (2)	ROCE (3)	Asset (4)	Liability (5)	Intangible Asset (6)	Operating Revenue (7)	Operating Cost (8)	Operating Profit (9)	R&D Expenditure (10)
ETS×Sector×Post	0.008	0.029	0.042**	-0.024	-0.025	-0.079	0.025	-0.013	0.023	-0.051
	(0.007)	(0.020)	(0.018)	(0.031)	(0.035)	(0.114)	(0.041)	(0.026)	(0.103)	(0.238)
Observations	21,527	21,338	21,183	21,531	21,530	21,531	21,531	21,527	18,143	12,767
R-squared	0.237	0.133	0.150	0.896	0.908	0.499	0.748	0.957	0.476	0.452
Firm attribute	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: All columns refer to the baseline DDD model Eq (1). ETS is a dummy for regional ETS pilots, Sector is a binary indicator for the covered sectors, and Post is a dummy for year 2011 and after. A set of fixed effects at firm, province-year, and industry-year is included. Standard errors presented in the parenthesis are clustered at industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 8: The Channel of the ETS Effect on Firm Financial Performance through Low Carbon Innovation Stock

VARIABLES	ROA		ROE		ROCE	
Region	Non-ETS Regions (1)	ETS Regions (2)	Non-ETS Regions (3)	ETS Regions (4)	Non-ETS Regions (5)	ETS Regions (6)
Panel A: One-year Time Window						
Sector×Post×Stock	0.001	0.016**	-0.001	0.037**	0.001	0.031**
	(0.004)	(0.006)	(0.016)	(0.016)	(0.009)	(0.014)
Observations	1,827	695	1,827	695	1,827	695
R-squared	0.235	0.376	0.166	0.275	0.196	0.409
Panel B: Two-years Time Window						
Sector×Post×Stock	-0.002	0.022	0.002	0.104*	-0.008	0.098*
	(0.004)	(0.017)	(0.017)	(0.061)	(0.011)	(0.055)
Observations	1,960	770	1,960	770	1,960	770
R-squared	0.226	0.385	0.204	0.266	0.338	0.392
Panel C: Three-years Time Window						
Sector×Post×Stock	-0.006	0.005	-0.034	0.054	-0.046	0.052
	(0.008)	(0.022)	(0.035)	(0.051)	(0.032)	(0.050)
Observations	1,984	781	1,984	781	1,984	781
R-squared	0.193	0.191	0.13	0.292	0.144	0.329
Firm Attributes	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y	Y	Y

Notes: Samples are divided into two groups: in the ETS regions and the non-ETS regions. The time window of averaging is one, two and three years, respectively. Dependent variables: ROA, ROE, and ROCE are the Return on Assets, Return on Equity, and Return on Capital Employed, respectively. Sector is a binary indicator for the covered sectors. Post is a dummy for year 2011 and after. Stock is the stock of low-carbon patents before the ETS policy was announced and took effect. Firm attribute includes firm age, asset, capital, revenue, operating cost, and knowledge stock.

A Online Appendix

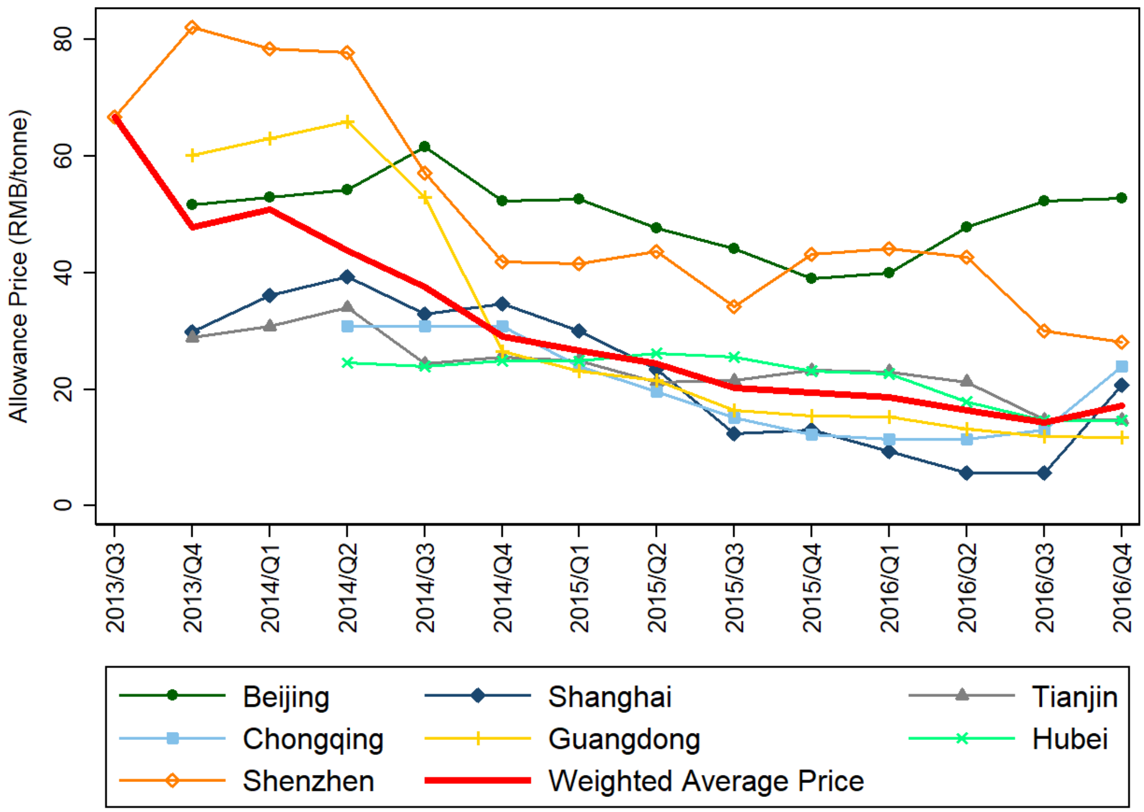

Figure A1: Carbon Price across Regional Pilots

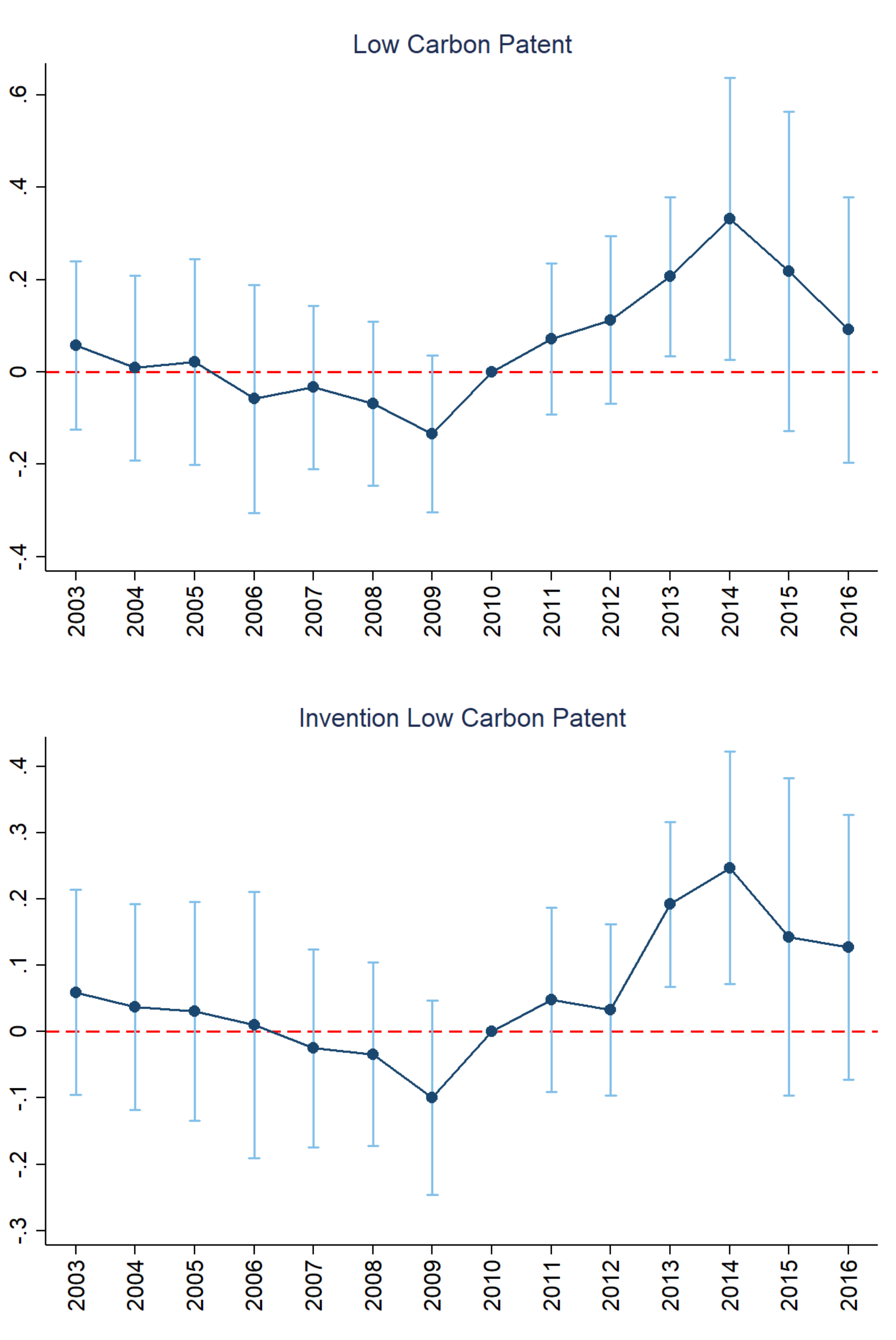

Figure A2: Dynamic Effect for Low-carbon Patent Count
Note: Charts from up to down show the dynamic impacts of ETS on low-carbon patent count and invention low-carbon patent count. Blue dots represent estimated coefficients of time-specific indicators, while vertical lines indicate the 95% confidence intervals. A variant of the baseline DDD regression specification (6) is conducted for firms' innovation outcomes.

Table A1: Summary of Covered Sectors across Pilots

Region	Announcement Year	Launch Year	Annual Allowance	Allowance Allocation	Covered Sectors	Threshold	Emissions Covered
Beijing	2011	2013	55Mt	Free allocation	Electricity, heating, cement, petrochemical other industries, large public buildings including hospitals, schools and governments	>10kt	40%
Chongqing	2011	2014	131Mt	Free allocation	Electricity, metallurgy, chemical industries, cement, iron and steel	>20kt	39.50%
Guangdong	2011	2013	388Mt	97% free allocation, 3% auction	Electricity, cement, steel, petrochemical industries, texile, paper making, aviation, public services including hotels, restaurants and business	2013: >20kt; since 2014: industries>10kt, non-industries > 5kt	58%
Hubei	2011	2014	324Mt	Free allocation	Electricity, heating, metallurgy, iron and steel, automobile and equipment, chemical and petrochemical industries, cement, medicine and pharmacy, food and beverage, papermaking	Energy consumption > 60k tce	33%
Shanghai	2011	2013	510Mt (3 years)	Free allocation	Electricity, iron and steel, petrochemical and chemical industries, metallurgy, building materials, papermaking, texile, aviation, airports and ports, public and office buildings, railway stations	Industries>20kt, non-industries > 10kt	57%
Shenzhen	2011	2013	30Mt	97% free allocation, 3% auction	Electricity, building, manufacturing, water supply	Industries >5kt, public building > 20k m^2, office builiding > 10k m^2	40%
Tianjing	2011	2013	100Mt	Free allocation	Electricity, hearing, iron and steel, chemical and petrochemical and industries, oil and gas exploration	> 20kt	60%

Sources: Zhang, Wang, and Du (2017).

Table A2: Descriptive Summary of Covered Sectors

Covered Sector	National Economic Industrial Classification	Share[1]
Building materials and cements	Non-metallic mineral products associated with building materials (parts of C30)[2]	2.74%
Chemical and petrochemical industries	Petroleum processing, coking and nuclear fuel processing industry (C25)	0.72%
	Chemical raw materials and chemical products manufacturing (C26)	7.10%
	Chemical Fiber Manufacturing (C28)	0.80%
	Rubber and plastic products industry (C29)	1.90%
Electricity and Heating	Power and heat production and supply (D44)	2.47%
Metallurgy, steel and iron	Ferrous metal smelting and rolling processing industry (C31)	1.18%
	Non-ferrous metal smelting and rolling processing industry (C32)	2.28%
	Metal products industry associated with steel and iron (parts of C33)[3]	0.57%
Oil and gas exploration	Oil and gas extraction industry (B07)	0.15%
	Oil and gas extraction and ancillary activities (B112)	0.57%
Papermaking	Paper and paper products industry (C22)	0.99%
Texile	Textile industry (C17)	1.48%
	Textile and apparel, apparel industry (C18)	1.14%
Water supply	Water production and supply (D46)	0.53%

[1] The last column denotes the ratio of observations in the covered sector relative to sample observations.
[2] This sector excludes graphite, glassware and ceramics not for building materials in the non-metallic mineral products industry (C30).
[3] This sector only includes steel and iron products in the metal products industry (C33).

Table A3: Baseline Regression Results for the ETS Effect on Share of Low-Carbon Innovation

	(1)	(2)	(3)	(4)	(5)
Panel A. Dependent Variable: Share of Low-carbon Patents in All Patents					
ETS×Sector×Post	0.021*	0.021*	0.020**	0.021*	0.021**
	(0.011)	(0.010)	(0.009)	(0.011)	(0.010)
R-squared	0.019	0.022	0.041	0.074	0.092
Panel B. Dependent Variable: Share of Low-carbon Patents in Invention Patents					
ETS×Sector×Post	0.025**	0.025**	0.025**	0.027**	0.029***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
R-squared	0.020	0.024	0.041	0.077	0.094
Observations	21,531	21,531	21,531	21,531	21,531
Firm Attributes		Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Province-Year FE			Y		Y
Industry-Year FE				Y	Y

Notes: All columns refer to the baseline DDD Eq (1). ETS is a dummy for regional ETS pilots, Sector is a binary indicator for the covered sectors, and Post is a dummy for year 2011 and after. Firm attribute includes firm age, asset, capital, revenue, operating cost, and knowledge stock. A set of fixed effects at firm, province-year, and industry-year are included. Standard errors in parenthesis are clustered at industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A4: Robustness Check for Patent Counts

	(1)	(2)	(3)	(4)	(5)
Panel A. Dependent Variable: Low-carbon Patents					
ETS×Sector×Post	0.198*	0.187*	0.179*	0.202*	0.205*
	(0.110)	(0.110)	(0.100)	(0.116)	(0.106)
R-squared	0.125	0.153	0.172	0.253	0.268
Panel B. Dependent Variable: Low-carbon Invention Patents					
ETS×Sector×Post	0.127	0.120	0.116	0.137*	0.142*
	(0.079)	(0.079)	(0.073)	(0.079)	(0.074)
R-squared	0.093	0.114	0.133	0.208	0.224
Observations	21,531	21,531	21,531	21,531	21,531
Firm Attributes		Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Province-Year FE			Y		Y
Industry-Year FE				Y	Y

Notes: All columns refer to the baseline DDD Eq (1). ETS is a dummy for regional ETS pilots, Sector is a binary indicator for the covered sectors, and Post is a dummy for year 2011 and after. Firm attribute includes firm age, asset, capital, revenue, operating cost, and knowledge stock. A set of fixed effects at firm, province-year, and industry-year are included. Standard errors in parenthesis are clustered at industry-province level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A5: Robustness Check: Balancing Test for Regulated and Unregulated Firms

	Unmatched Sample 207 treated vs 2,022 control			Matched Sample 134 treated vs 123 control		
VARIABLES	Treated (1)	Control (2)	P-value (3)	Treated (4)	Control (5)	P-value (6)
Asset	22.819	21.548	0.000	22.394	22.381	0.940
Capital	22.080	20.964	0.000	21.693	21.66	0.822
Revenue	22.353	20.932	0.000	21.890	21.866	0.897
Total Patent	2.926	1.819	0.000	2.814	2.558	0.275
Total Patent Stock	4.089	2.820	0.000	3.934	3.787	0.569
Low Carbon Patent	0.860	0.354	0.000	0.752	0.641	0.411
Low Carbon Patent Stock	1.513	0.724	0.000	1.372	1.280	0.619

Table A6: Placebo Tests: Baseline DDD

DEPENDENT VARIABLES	Share of Water Pollution Patents in All Patents		Share of Non Low-carbon Patents in All Patents	
	(1)	(2)	(3)	(4)
ETS×Water_cai×Post	-0.003		-0.024	
	(0.002)		(0.067)	
ETS×Water_census×Post		0.002		-0.016
		(0.005)		(0.032)
Observations	21,531	21,531	21,531	21,531
R-squared	0.101	0.101	0.268	0.268
Firm FE	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y

Notes: All columns refer to a variant of the baseline DDD model Eq (1), where ETS is binary indicator for the ETS regions, Post is indicator for ETS post period, Water_cai and Water_census are two alternative binary indicators for water-pollution-intensive sectors. The former is taken from Cai, Chen, and Gong (2016), while the latter is reported by the Census of Pollution Statistics Survey. Firm attribute includes firm age, asset, capital, revenue, operating cost, and knowledge stock. A set of fixed effects at firm, province-year, and industry-year is included. Standard errors presented in the parenthesis are clustered at industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A7: Extension: The Crowding-out Effect for Other Technologies

DEPENDENT VARIABLES	Share of Water Pollution Patents in All Patents (1)
Panel A. Baseline DDD model	
ETS×Sector×Post	0.003
	(0.003)
R-squared	0.101
Panel B. Carbon Market Model	
ETS×Sector×$I(2011 \leq \text{Year} \leq 2012)$	0.004
	(0.003)
ETS×Sector×$I(\text{Year} \geq 2013)$×Price	0.002
	(0.002)
R-squared	0.101
Panel C. Listed Firms' Exposure to ETS and Carbon Price	
Exposure×$I(2011 \leq \text{Year} \leq 2012)$	0.004
	(0.004)
Exposure×$I(\text{Year} \geq 2013)$×Price	0.004
	(0.003)
R-squared	0.102
Observations	21,531
Firm Attributes	Y
Firm FE	Y
Province-Year FE	Y
Industry-Year FE	Y

Note: Panel A refers to the baseline DDD model Eq (1), Panel B denotes the carbon market model Eq (5), and Panel C is the listed firms' exposure model Eq (2) while accounting for carbon market prices. Firm attribute includes firm age, asset, capital, revenue, operating cost, and knowledge stock. A set of fixed effects at firm, province-year, and industry-year is included. Standard errors presented in the parenthesis are clustered at industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.