Carbon Price, Innovation, and Firm Competitiveness*

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Abstract

Using China's regional carbon market pilots as a natural experiment, we examine the impacts of the emission trading system (ETS) on firms' innovation and competitiveness. We show that the ETS directs innovation towards climate-friendly technologies; it increases the climate patent ratio by 2.1 percentage points, equivalent to a 20.5 percent increase in the total climate patent counts. We find no evidence that the ETS harms firms' profitability and productivity, partly due to the beneficial effect of climate innovation. We demonstrate early climate innovators can gain competitive advantages after the ETS launch. The climate patents accumulated before the ETS enable regulated firms to improve total factor productivity and financial performance.

Keywords: Emission Trading System, Innovation, Firm Competitiveness.
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1 Introduction

The major economies have used market-based climate policy instruments, such as emissions trading systems (ETS) or carbon tax, to achieve cost-effective climate mitigation. The World Bank (2022) reports that 46 countries or regions have implemented 68 carbon pricing initiatives, mostly the carbon ETS, to regulate 23.1% of global greenhouse gas (GHG) emissions.[1] While carbon pricing allows a firm to choose its path of compliance flexibly (Fan, Chen, and Chen, 2022), its economic consequence is uncertain. On the one hand, carbon price increases business costs associated with changing energy sources, production processes, and management practices. On the other hand, carbon prices can induce climate-friendly innovation and may even improve firm performance. Firm competitiveness is a primary concern for countries to deep-decarbonize their economies; however, it is debatable how carbon pricing affects firm innovation, profitability, and productivity.

This paper addresses two research questions. Is the carbon ETS effective in inducing firms' innovation of climate-friendly technologies? Can firms gain a competitive advantage from climate innovation? We use China's regional ETS pilots to answer these questions. As the world's largest GHG emitter, China is tapping the carbon market to meet its ambitious climate pledge. Understanding the economic impacts of the ETS on firms is instrumental for China to make a more aggressive and meaningful climate commitment. Methodologically, China's regional ETS pilots provide an excellent natural experiment. Using the regulatory variations across regions, sectors, and time, we employ a difference-in-difference-in-differences (DDD) approach to identify the ETS effect on firm innovation and competitiveness. To conduct the empirical analysis, we have compiled a comprehensive dataset for China's publicly listed firms and their subsidiaries, including detailed firm-level information about patents granted in all technological fields and economic fundamentals.

[1] The EU ETS, launched in 2005, is the first and largest major carbon emission trading system in the world. Although no national ETS exists in the US, 9 Northeast states formed the Regional Greenhouse Gas Initiative 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.

We demonstrate unambiguous evidence that China's ETS accelerates the innovation of carbon-reducing technologies. Specifically, the ETS increases the climate patent ratio by 2.1 percentage points or 20.5 percent in patent counts. To put it in context, this induced-innovation effect of China's ETS is on par with the EU ETS.[2] The effect is more pronounced for high-quality patents than for incremental ones.[3] A higher carbon price can also create more incentives for climate innovation. Furthermore, we find no evidence that the ETS harms firms' profitability and productivity. We explore the channel of innovation through which the ETS affects firm competitiveness. The empirical results show that carbon-intensive firms in the ETS regions that banked more climate patents before the ETS can gain competitive advantages once the ETS comes into effect. In addition, climate innovation enables firms to reduce capital inputs and total wages while maintaining similar output levels. These results suggest climate innovation can benefit ETS-regulated firms by reducing compliance costs or selling carbon allowances in the carbon market.

This paper is the first to study how the innovation induced by the ETS affects firm competitiveness in China's regional ETS pilots. The existing papers in a similar empirical setting (Cui, Zhang, and Zheng, 2018; Zhu et al., 2019; Cui et al., 2021; Cao et al., 2021) have not yet explored the link between innovation and firm competitiveness. The paper contributes to the growing literature on the effect of market-based instruments in inducing climate technology innovation (Martin, Muûls, and Wagner, 2012; Taylor, 2012; Borghesi, Cainelli, and Mazzanti, 2015; Calel and Dechezleprêtre, 2016; Calel, 2020).[4] The paper also contributes to the debate on the impacts of carbon pricing on firms' financial performance (Veith, Werner, and Zimmermann, 2009; Commins et al., 2011; Bushnell, Chong, and Mansur, 2013; Borghesi, Cainelli, and Mazzanti, 2015; Marin, Marino, and Pellegrin, 2018).

[2] Calel and Dechezleprêtre (2016) finds that a 10% 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% increase in low-carbon patenting and R&D spending for regulated British firms during the 2000-2012 period.

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

[4] 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; Johnstone, Haščič, and Popp, 2010) and how environmental regulation incentivizes innovation and diffusion of pollution abatement technologies (Popp, 2003, 2006; Dechezleprêtre and Glachant, 2014).

We provide new empirical evidence for the hypothesis that a properly designed environmental regulation can improve firm competitiveness through innovation (Porter and van der Linde, 1995). Our finding also supports the theory that climate policies direct technical changes toward factor-saving technologies (Acemoglu et al., 2012).

This paper is the first attempt to measure firms' exposure to the ETS by sorting out listed firms' entire corporate tree structures in China, considering that a parent firm can have subsidiaries in multiple regions or sectors (Hanna, 2010; Giroud and Mueller, 2015, 2019; Cui and Moschini, 2020). Furthermore, we make a substantial data contribution by constructing a unique China Patent Project analogous to the NBER Patent Data Project.[5] Our data project that integrates detailed patent information of China's listed firms and their subsidiaries can be applied to various research in firm innovation.

Our analysis also provides important insights for China to meet its climate commitment: peaking carbon emissions by 2030 and aiming for carbon neutrality by 2060. Under the carbon price in the sample period ($4.2/ton), the innovation induced by the ETS contributes to a 1.66% decrease in carbon intensity. If China increases the carbon price to the social cost of carbon (Nordhaus, 2019), i.e. $50/ton, it can increase climate patenting by 91.72% and hence reduces emission intensity by 7.43%. The back-of-the-envelope calculation suggests that as China tightens its carbon emission regulations, the induced innovation can help China achieve its climate ambition while minimizing compliance costs.

The remainder of the paper is organized as followers. Section 2 introduces the empirical strategy to identify the ETS impacts on firm innovation and financial performance. Section 3 presents data and variables. Section 4 presents empirical results on climate innovation. Section 5 presents the results on firm profitability and productivity. Section 6 discusses policy implications. Section 7 concludes.

[5]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.

2 The ETS Impacts on Firms

2.1 Literature

The primary goal of an ETS is to incentivize firms to reduce carbon emissions. The abatement effect is evident for a cap-and-trade system like the EU ETS. Colmer et al. (2022) finds that the EU ETS leads to an 8-12% reduction in carbon emissions for regulated firms compared to unregulated counterparts. However, the effect is less obvious for a tradable performance standard, such as China's regional ETS pilots, which regulate emission intensity instead of total emissions (Pizer and Zhang, 2018; Goulder et al., 2019). Cui et al. (2021) provides the first comprehensive evidence that the pilot ETS leads to a 16.7% reduction in carbon emissions from regulated firms. Cao et al. (2021) suggests that emission reduction is mainly achieved by reducing 16% of coal consumption for regulated power plants. In addition, Yong et al. (2021) examines the impacts of two ETS pilots in Beijing and Hubei on management practices using survey interviews with plant managers and engineers. Their findings suggest an overall reduction of electricity and coal for treated firms with better management efficiency in these two pilots.

The advantage of an ETS over prescriptive regulatory measures is to minimize the cost of abatement. The ETS allows a regulated firm to choose its compliance paths to achieve cost-effective emission reductions, such as fuel switching, energy conservation, and efficiency improvement. Nevertheless, the ETS still imposes an additional cost burden on firms. The literature is ambiguous about the financial impacts of the ETS. Commins et al. (2011) finds that the EU ETS in the first phase has some negative effects on firms' profitability and productivity but not on employment and investment. In a more comprehensive assessment, Marin, Marino, and Pellegrin (2018) finds no evidence that the first and second phases of the EU ETS negatively affect firms' financial performance. Using carbon price to indicate the stringency of the ETS, Veith, Werner, and Zimmermann (2009) and Bushnell, Chong, and Mansur (2013) document the positive relationship between carbon prices in the EU ETS and stock returns of firms in power sectors; this is likely caused by regulated firms passing costs through to their customers.

The cost-saving effect of an ETS is also enabled by its stimulation of climate innovation. If the ETS is expected to be persistent, regulated firms are incentivized to engage in the innovation of low-carbon technologies to achieve more cost-effective emission reductions in the long run. The empirical evidence for the ETS impacts on product and process innovations is mixed. Based on responses from manager interviews, Martin, Muûls, and Wagner (2012) shows no significant differences in clean product and process innovations between regulated and unregulated firms in the EU ETS. On the contrary, using a sample of Italian manufacturing firms from the 2006-2008 Community Innovation Survey dataset, Borghesi, Cainelli, and Mazzanti (2015) documents a positive correlation between the EU ETS participation and innovation for carbon emission reductions and energy efficiency improvement.

The literature generally agrees that the ETS can stimulate climate patenting. For example, the US NO_x and SO_2 cap-and-trade programs incentivize firms to invest in patenting activities (Taylor, 2012). The EU ETS contributes to a 10% increase in low-carbon patents during the 1979-2009 period (Calel and Dechezleprêtre, 2016). In particular, 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 (Calel, 2020). Empirical evidence is also emerging in China. Cui, Zhang, and Zheng (2018) first reports that carbon pricing stimulates climate patenting for publicly listed companies. Zhu et al. (2019) provides corroborative evidence using the Chinese Annual Survey of Industrial Firms.

2.2 China's Regional ETS Pilots

China has adopted market-based instruments, especially the ETS, to curb its ever-increasing carbon emissions cost-effectively. On October 29th, 2011, China's National Development and Reform Commission (NDRC) approved seven regional carbon market pilots in Beijing, Shanghai, Tianjin, Chongqing, Guangdong, Hubei, and Shenzhen.[6] The pilot regions are granted flexibility in designing their own carbon market rules following some general guidelines from the NDRC. Each pilot can determine covered sectors, emissions targets, allowance allocation, monitoring, reporting and verification (MRV), and compliance, while the NDRC oversees the planning and development of ETS (Zhang, Wang, and Du, 2017). Table A1 in the Online Appendix summarizes the regional ETS policies across pilots.

China's regional ETS pilots provide a natural experiment to identify the causal relationship between the ETS and firm competitiveness. First, among 34 provincial-level jurisdictions in China, the ETS pilots include two provinces (Guangdong and Hubei), four municipalities (Beijing, Shanghai, Tianjin, and Chongqing), and one special economy zone (Shenzhen). ETS pilots differ in sector inclusion, total allowances, allowance allocation rules, and MRV systems, leading to significant heterogeneity across pilots.[7] Such substantial regional variations allow us to compare firm-level climate innovation and financial performance between ETS and non-ETS regions. Second, the seven pilots regulate different manufacturing and public utility companies. This sectoral variation allows us to compare firm-level outcomes between covered and non-covered sectors. Third, the ETS pilots experienced two important periods: announcement (2011 to 2012) and allowance trading (since 2013).[8] During the announcement period, the sector coverage and detailed implementation rules were subject to considerable uncertainty. The announcement effect on climate innovation would likely differ significantly from the ETS effect after the trading starts.

2.3 Identification

Since China's regional ETS pilots regulate firms in the covered sectors in the seven jurisdictions after 2011, it is natural to adopt the difference-in-difference-in-differences approach to

[6]Shenzhen is part of Guangdong, but they launched an independent regional carbon market pilot.

[7]In the Appendix, we provide a detailed description of the institutional background of China's regional ETS pilots.

[8]Shenzhen was the first ETS pilot launched in June 2013, followed by Shanghai, Beijing, Guangdong, and Tianjin in the same year. The remaining pilots, Hubei and Chongqing, launched ETS in April and June 2014, respectively.

identify the causal effect of the ETS on firms' climate innovation and financial performance. Taking advantage of variations across regions, sectors, and time, we can compare the treatment and control groups using the triple differences approach. We are concerned with the contemporary shocks that might differently target the treatment or control groups in the study period. Although we cannot test this identification assumption directly, we conduct analyses to assess the influence of some possible coinciding shocks. Below we discuss the strategies to address potential threats to our identification's validity.

The first threat is from the contemporary environmental policies that target overlapping regions. In 2013, the Ministry of Ecology and Environment[9] 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 incentivize innovation similar to the carbon ETS. To address this concern, we drop the firms from BTH in the sensitivity analysis.

The second threat is from the innovation subsidies. These policies include a national favorite tax rate policy for high-tech firms,[10] a low-carbon special fund in Shenzhen, and a national energy subsidy policy for 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. To account for innovation incentive policies, we also drop the certified high-tech firms in renewable energy, energy conservation, resources, environmental technologies, new materials, and electronics engineering.

The third threat is that the entry and exit of firms might change the composition of treatment and control groups. The exit of firms is a minor concern since China seldom

[9] Formerly the Ministry of Environmental Protection.

[10] The innovation incentive reduces the tax rate for high-tech firms from 25% down to 15%.

delisted publicly listed firms in China except for only a few cases.[11] In terms of entry, new firms with climate 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, which 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 propensity score matching (PSM) with the DD approach. The DD approach defines all the regulated firms as the treatment group, and the unregulated firms serve as the control group. This approach helps us test the stability of the DDD results against alternative designations of the treatment group. Furthermore, in the PSM-DD approach, we match the regulated firms with unregulated ones based on their pre-ETS economic characteristics. With this restricted matched sample, we adopt a variant of the DD method to examine the effect of the ETS on climate patenting. See Section A.3 in the Online Appendix for more details.

3 Data and Variables

3.1 Data Sources

We have assembled a comprehensive dataset of economic and innovation activities for China's listed firms and their subsidiaries between 2003 and 2016. The data cover the manufacturing and utility sectors, integrating detailed firm-level information about patents granted in all technological fields 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

[11] 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 implicit 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's stock markets had been delisted by 2016.

firms and shareholdings.[12] The State Intellectual Property Office (SIPO) of China supplies detailed patent information, including application number, application date, grant number, grant date, and primary International Patent Classification (IPC) code.[13] 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 China's listed firms and subsidiaries with those 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; Chongqing and Hubei started trading in Q2 2014. Therefore, the carbon price data are available between Q3 2013 and Q4 2016, the end of our sample period. Figure A1 plots quarterly carbon prices across regional pilots.

Ultimately, our data contain 21,531 firm-year observations associated with 2,142 unique listed firms and 57,842 subsidiaries. In the study period, around 0.9 million patent applications were successfully granted, and roughly less than 8% of patents were related to climate technologies. Parent firms own 0.4 million patents among all granted patents, while the remaining patents are owned by subsidiaries.

3.2 Variables

ETS. The primary explanatory variable is the treatment status of listed firms. The seven regional pilots cover a range of carbon-intensive manufacturing and public utility sectors, including electricity, heating, iron and steel, chemical, petrochemical, cement, metallurgy, paper making, textile, oil and gas exploitation, and water supply. We define the covered sectors as those carbon-intensive manufacturing and public utilities that appeared in any

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

[13] In 1980, China founded its patent office, the SIPO, and adopted a patent system similar to those used in Europe and Japan. On August 28th, 2019, China's SIPO was renamed China National Intellectual Property Administration.

pilot region. We then correspond the covered sectors with the two-digit industry codes. Table A1 in the Online Appendix summarizes the covered sectors and standard industrial classifications. In the robustness checks, we narrow the classification of covered sectors to those carbon-intensive sectors chosen by most regional ETS pilots.

To better measure the regulatory exposure for parent firms with subsidiaries in various regions and sectors, we retrieve the corporate tree information 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 the ETS.

Climate patenting. We use climate patent ratios and counts as a proxy for firms' climate innovation. China grants three types of patents: invention, utility model, and design. Invention and utility model patents, whose IPC codes align with the World Intellectual Property Organization (WIPO), are most relevant to climate-friendly technologies.[14] The invention patents substantively examined by the SIPO represent practical, inventive, and new technical innovations. 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 critical innovations in China's patent system (Liu and Qiu, 2016; Hu, Zhang, and Zhao, 2017; Wei, Xie, and Zhang, 2017). In the analysis, we use the climate patent ratio (the share of climate patents in all patents) and climate invention patent ratio (the share of climate patents in invention patents) as the main dependent variables.

To classify climate-friendly technologies, we match each granted patent's primary IPC code with the IPC Green Inventory code 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).[15] We

[14] 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.

[15] The European Patent Office (EPO) has recently developed a new category of IPC codes, dubbed as the Y02 class, about technologies or applications for mitigation or adaptation against climate change (Haščič

define climate innovation as technologies associated with alternative energy production, energy conservation, and waste management. We also conduct robustness checks by narrowing the definition to only alternative energy production and energy conservation.

Firm profitability. We measure a firm's financial performance by three indicators: return on assets (ROA), return on equity (ROE), and return on capital employed (ROCE). ROA, defined by the ratio of net income to total assets, focuses on the financial efficiency of assets. ROE, calculated by dividing net income by average shareholder's equity, captures the return on net assets. ROCE, calculated by dividing the earnings before interest and tax by total capital employed, represents the utilization efficiency of a firm's available capital. The three indicators are widely used to evaluate firms' profitability.

Firm productivity. The firm-level total factor productivity (TFP) is estimated by two methods (Olley and Pakes, 1996; Levinsohn and Petrin, 2003). The TFP estimated by the Olley-Pakes method (TFP-OP) is based on revenues, capital, wages, and investment at the two-digit industry level. We also compute an alternative TFP measure by the Levinsohn-Petrin method (TFP-LP), which adopts intermediate inputs to proxy the unobserved productivity shock. The second approach captures firms' business growth.

Summary statistics. The final dataset contains 21,531 firm-year observations with 2,142 unique listed firms and their 57,842 subsidiaries. Table 1 reports the summary statistics for the variables used in the empirical analysis, including several measures of climate innovation, financial performance, firm attributes, and regional carbon prices.

[Insert Table 1 about here]

We use a sample mean analysis to compare climate patenting for the regulated and unregulated sectors. Table A2 summarizes the results. We find that the sectors subject to the ETS policy increase the climate patent ratio by 1.6 percentage points; the magnitude

and Migotto, 2015; Calel and Dechezleprêtre, 2016). This list of climate technologies includes, for example, efficient combustion technologies, carbon capture and storage, efficient electricity distribution, and alternative energy production. Although China's SIPO has not adopted the Y02 class yet, we have cross-checked the sub-class of this Y02 class with the IPC Green Inventory and found some similarities between these two classification systems. Our results are robust to the alternative definition of climate technologies.

of the effect is the same for the climate invention patent ratio. This statistically significant DDD estimate suggests that the regional ETS pilots direct sectoral innovation activities toward climate-friendly technologies.

4 Climate Innovation

4.1 The ETS Effect on Climate Patenting

We first study the impact of regional ETS pilots on firm climate innovation. For listed firm i in sector j from region r at year t, the relationship between the ETS and climate patenting Y_{ijrt} is given by the following triple differences model

$$Y_{ijrt} = \beta_1 \text{ETS}_r \cdot \text{Sector}_j \cdot \text{Post}_t + \gamma' X_{it} + \lambda_i + \delta_{jt} + \eta_{rt} + \varepsilon_{ijrt}. \tag{1}$$

In this form, the treatment status of a listed firm depends on its region, sector, and time: ETS_r is an indicator for pilot regions, Sector_j is an indicator for covered sectors, and Post_t is a time dummy for the year 2011 and after. Correspondingly, β_1 is the parameter of central interest reflecting the ETS's impact on regulated firms. Other control variables, denoted by X_{it}, include time-varying firm attributes, such as age, asset, capital, revenue, and operating cost. The firm-specific fixed effect, λ_i, controls for the firm-level unobservables that affect climate patenting. The sector-by-year specific effect, δ_{jt}, controls for the national industrial policies across provinces, such as renewable energy subsidies. The region-by-year specific effect, η_{rt}, controls for the region- and time-varying factors influencing innovation, such as the provincial innovation policies. Finally, ε_{ijrt} is an unobserved error term.

We use patents as a proxy for firm innovation following the literature (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. We use the climate patent ratio to indicate firm climate innovation. To differentiate the quality of innovation, we employ the climate invention patent ratio as a primary dependent variable for high-quality innovation activities. We use ratios instead of counts to mitigate the concern that climate innovation and other innovative activities are subject to the same policy shocks (Popp, 2002). As a robustness check, we also run the same regression using climate patent counts.

We estimate the baseline model in Eq (1) using the firm-level data. Table 2 presents the results. The regression framework allows us to control for observable time-varying firm attributes and a set of fixed effects at the firm, industry-by-year, and province-by-year levels.[16] In the main regressions, standard errors are clustered at the sector level. Columns (1)-(3) report the results for the climate patent ratio. The estimate in column (1) suggests that the ETS increases the climate patent ratio by 2.1 percentage points, statistically significant at the 5% level. The estimate's economic significance shall not be downplayed since the average climate patent ratio in the entire sample is 3%.

[Insert Table 2 about here]

China announced the carbon market pilots in 2011; it determined the allowance allocation rules and formally started carbon allowance trading in 2013. Therefore, we differentiate the ETS effects into two periods. In the trading period, carbon prices provide essential signals for regulatory stringency. This leads to the following specification:

$$\begin{aligned} Y_{ijrt} =& \beta_1 \text{ETS}_r \cdot \text{Sector}_j \cdot I(2011 \leq t \leq 2012) + \beta_2 \text{ETS}_r \cdot \text{Sector}_j \cdot I(t \geq 2013) \cdot \text{Price}_{rt} \\ &+ \gamma' X_{it} + \lambda_i + \delta_{jt} + \eta_{rt} + \varepsilon_{ijrt}. \end{aligned} \tag{2}$$

The estimation results are reported in columns (2)-(3) of Table 2. The coefficient estimates for the two periods are positive and statistically significant. As expected, column (2) shows

[16]Including the fixed effects and firm attributes one by one does not alter the main conclusion. The results are presented in panels A and B in Table A3 in the Online Appendix.

that the ETS effect in the trading period is greater than in the announcement period. In addition, column (3) suggests that a one-dollar increase in carbon price boosts the climate patent ratio by one percentage point, which is significant at the 1% level. The result suggests that a higher carbon price sends a stronger signal for climate patenting.

We further test the ETS effect on innovation quality by focusing on more substantive innovation. Columns (4)-(6) of Table 2 report the ETS effect on the climate invention patent ratio, i.e., the share of climate patents in invention patents. The estimates are qualitatively similar to the climate patent ratio, but the magnitudes become large. The ETS increases the climate invention patent ratio by 2.9 percentage points; one dollar increase in carbon price increases the climate invention patent ratio by 1.1 percentage points. The result suggests that the ETS creates more incentives for substantive innovation.

4.2 Dynamic Effects

The identification assumes that the pre-existing differences in climate patenting for the treated and control groups are orthogonal to the ETS. China's regional ETS pilots regulate emission-intensive entities in developed provinces or cities. There are systematical differences in innovation activities between the treatment and comparison firms. Therefore, the fundamental identification assumption is that these differences are invariant across time for the DDD approach to yield a consistent estimate of the ETS effect. To check the validity of this assumption, we estimate the following dynamic effects model controlling for the lags and leads of the policy year dummies:

$$\begin{aligned} Y_{ijrt} = & \sum_{m=1}^{7} \beta_{1m} \mathrm{ETS}_r \cdot \mathrm{Sector}_j \cdot \mathrm{Post}_{t-m} + \sum_{n=1}^{5} \beta_{2n} \mathrm{ETS}_r \cdot \mathrm{Sector}_j \cdot \mathrm{Post}_{t+n} \\ & + \gamma' X_{it} + \lambda_i + \delta_{jt} + \eta_{rt} + \varepsilon_{ijrt}. \end{aligned} \tag{3}$$

In this form, Post_{t-m} is a pre-policy dummy indicating the m^{th} lag of the 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 the treatment effect in the years after the ETS launch.

We test the assumption that the patenting trends for the regulated firms and the comparison group were similar before the ETS by estimating Eq (3). Figure 1 illustrates the point estimates and 95% confidence intervals for the estimated dynamic effects. It suggests that the trends of climate patenting were not statistically different between the regulated and non-regulated firms before the ETS.

[Insert Figure 1 about here]

4.3 Corporate Regulatory Exposure

A large company may can multiple subsidiaries with different treatment statuses depending on the sector, location, and time. We define a parent company's exposure to the ETS as a function of its subsidiaries' exposures. As a result, below is a more generalized specification for evaluating the ETS effect on climate patenting:

$$Y_{ijrt} = \beta_1 \text{Exposure}_{it} + \gamma' X_{it} + \lambda_i + \delta_{jt} + \eta_{rt} + \varepsilon_{ijrt}, \tag{4}$$

where Exposure_{it} is an alternative measure of the policy treatment. Following the approach proposed by Hanna (2010),[17] we consider parent firm i's exposure to the ETS as the (weighted) average of all its subsidiaries' exposures:

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

[17] 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.

where N_{it} is the number of subsidiaries for firm i; dummy variable ETS_{nr} designates subsidiary n located in one ETS region; 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.

Following Eq (2), we can decompose the ETS effects in two periods for the regulatory exposure model as follows:

$$\begin{aligned} Y_{ijrt} =& \beta_1 \text{Exposure}_{it} \cdot I(2011 \leq t \leq 2012) + \beta_2 \text{ExposurePrice}_{it} \cdot I(t \geq 2013) \\ &+ \gamma' X_{it} + \lambda_i + \delta_{jt} + \eta_{rt} + \varepsilon_{ijrt}. \end{aligned} \tag{5}$$

Let Price_{rt} designate the region-specific price of carbon allowances. The ETS exposure in the trading period can incorporate carbon price as a proxy for regulatory stringency:

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

Table 3 presents the estimation results for Eqs (4) and (5). The results in columns (1) and (4) are similar to the main conclusion. It suggests that as more subsidiaries from a listed firm are covered by the ETS, the ETS-induced innovation effect becomes stronger. We also decompose the ETS effects by two periods and report the results in columns (2)-(3) and (5)-(6) in Table 3. The findings are similar to the main results. In all columns, the coefficient estimates for ETS exposure in the announcement period are positive and significant, but their magnitudes are smaller than those in the trading period. In addition, the estimates confirm that higher carbon prices create more incentives for innovation. Overall, the regulatory exposure model yields similar results as the baseline specification.

[Insert Table 3 about here]

4.4 Robustness

Figure 2 summarizes the robustness checks. First, we test the sensitivity of our results regarding potential confounders. We drop the samples from Beijing, Tianjin, and Hebei to test the effect of regional air pollution control policies (row b), drop PV patents to test the potential impact of PV innovation subsidies (row c), and drop high-tech firms to test the potential impact of the nationwide tax incentives for innovation (row d). Second, we test several alternative specifications. We use two-year forward patents as an outcome variable to account for time lags in innovation (row e). We limit climate patents to alternative energy production and energy conservation (row f).[18] We collapse the data into two periods and re-run the baseline regression (row g).[19] We cluster the standard errors at the industry-province level (row h). We control for province-industry fixed effect (row i). We narrowed the treatment group to the most carbon-intensive industries (electricity, heating, steel and iron, cement, and petrochemical) covered by more than five ETS pilots (row j). We also measure the ETS exposure by the weighted average of all its subsidiaries' exposures (row k). Third, we employ alternative identification strategies using DD (row l) and PSM-DD (row m). Overall, none of these tests changes the main conclusion.

[Insert Figure 2 about here]

In addition to the above robustness checks, we use water pollution as a placebo test to rule out the possibility that climate innovation is driven by factors other than the ETS. The test is described in Section A.4 in the Online Appendix. We further consider innovation quality using patent counts weighted by the number of future citations received. Section A.5 in the Online Appendix provides the corresponding results. Last, we examine the ETS effect on patent counts instead of ratios. Panels C and D of Table A3 in the Online Appendix present the corresponding results varying by fixed effects. For the preferred specification

[18] It is in line with the EPO classification of climate technologies under the new category of the Y02 class.

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

in the last column, the ETS contributes to a 0.205 percentage point increase in all climate patents. Figure A2 in the Online Appendix illustrates the estimated dynamic effects for patent counts. We found no evidence that the trends of climate 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 Firm Competitiveness

5.1 The ETS Effect on Profitability and Productivity

We are concerned about the effects of the ETS on firm competitiveness, such as profitability and productivity. We use return on assets, return on equity, and return on capital employed as the primary indicators for a firm's profitability. Following the baseline specification in Eq (1), we estimate the ETS impacts on firms' financial performance. Columns (1)-(3) in Table 4 report the estimation results. The estimates suggest that the ETS has statistically insignificant effects on ROA and ROE, while the estimate is positive and statistically significant at the 5% level for ROCE.

[Insert Table 4 about here]

We also estimate the impact of the ETS on firm-level total factor productivity, measured by the Olley-Pakes method (TFP-OP) or the Levinsohn-Petrin method (TFP-LP). Columns (4)-(5) in Table 4 report the results. The estimates are positive but statistically insignificant, suggesting the muted impacts of the ETS on firm productivity. To summarize, although we cannot claim that China's ETS pilots increased firm profitability and productivity, the bottom line is that we find no evidence that it harmed firm competitiveness.

5.2 Innovation and Profitability

Climate innovation can mitigate a firm's regulatory burden of the ETS. More innovative firms can financially benefit from climate innovation by abating carbon emissions with lower costs or selling carbon allowances in the carbon market. To test this hypothesis, we examine whether a firm that banked more climate patents before the ETS would have an early mover advantage once the ETS comes into effect. We model financial performance y_{ijrt} for firm i in sector j from region r at year t as:

$$y_{ijrt} = \beta_1 \text{Stock}_i \cdot \text{Sector}_j \cdot I(t \geq 2011) + \gamma' X_{it} + \lambda_i + \delta_{jt} + \eta_{rt} + \varepsilon_{ijrt}. \tag{6}$$

In this model, Stock_i represents the number of climate patents accumulated before the announcement of the ETS pilots. Sector_j is a binary variable denoting carbon-intensive sectors that would be covered under the ETS after 2011. The time dummy, $I(t \geq 2011)$, indicates the post-ETS period. Other variables are the same as the baseline specification in Eq (1). The coefficient of the triple interaction term, β_1, measures the effect of the pre-ETS climate patent stock on the post-ETS financial performance of carbon-intensive firms.

Considering innovation takes time, we collapse the samples into two periods by averaging one-, two-, and three-year observations before and after 2011. Over the pre- and post-ETS periods, we calculate average firm-level variables, including profitability indicators, productivity measures, covariates, and climate patent stocks. Using the collapsed two-period data, we run the regression in Eq (6) on the split samples for the ETS and non-ETS regions separately. We expect climate patents do not affect firms in the non-ETS regions but benefit those in the ETS regions. Table 5 reports the estimation results.

[Insert Table 5 about here]

For the non-ETS regions (odd columns), the climate patent stock accumulated before the announcement of the ETS has muted or even negative impacts on ROA, ROE, and

ROCE for carbon-intensive firms after 2011, barring statistical significance. This result is intuitive since climate innovation can not turn into profit by itself in the absence of a carbon price. In sharp contrast, for the ETS regions (even columns), the pre-ETS climate patent stock positively impacts the profitability of carbon-intensive firms after 2011. Most of these estimates are statistically significant. The difference in the estimates between the ETS and non-ETS regions suggests an advantage for early innovators. We also find that the early-mover advantage increases over time. In the ETS regions, the estimated coefficients are insignificant for the one-year window. As the time window expands from two to three years, the magnitude and significance of these estimates become more pronounced.

5.3 Innovation and Productivity

We explore how the ETS affects firm productivity through the channel of climate innovation. Table 6 shows the estimates based upon the specification in Eq (6). Columns (1)-(2) present the results for TFP-OP, and columns (3)-(4) for TFP-LP. In the non-ETS regions, the pre-ETS climate patent stock has muted impacts on post-ETS productivity for carbon-intensive firms. These estimates remain insignificant across different time windows. Since carbon-intensive firms are regulated in the ETS regions after 2011, the result suggests that climate innovation does not affect unregulated firms' productivity significantly.

[Insert Table 6 about here]

On the contrary, in the ETS regions, the pre-ETS climate patent stock has some modest and positive impacts on post-ETS productivity for carbon-intensive firms. These positive estimates are statistically significant at the 10% level for the TFP-OP for all the time windows. The estimates for the TFP-LP are statistically significant for the two- and three-year time windows. Another notable finding is the rising magnitude of these estimates as the time window expands. These results suggest that climate innovation can boost the productivity of carbon-intensive firms under the ETS.

6 Discussion

China has gradually become active in global climate mitigation since it overtook the US as 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 following 12th Five-Year Plan (2011-2015), a blueprint for China's overall social and economic development, embodied the carbon emission target. In the 2015 Paris Agreement. China committed to reducing 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 demonstrates China's long-term commitment to tackling the challenge of global climate change.

Technological change 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 climate innovation, which reduces the cost of compliance with its climate commitments. Our analysis demonstrates unambiguous evidence that the ETS stimulates climate patenting. Costantini et al. (2017) finds 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 climate patents by around 20.5%. A back-of-the-envelope calculation suggests that the ETS can lead to a 1.66% 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 climate patents by 21.85%, leading to a 1.77% decline in carbon intensity. If carbon price reaches the level of the social cost of carbon ($50/ton) (Nordhaus, 2019), it will further increase climate patenting by 91.72% and hence give rise to a reduction in emission intensity by 7.43%.[20]

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

Our results provide important policy implications for China's national carbon ETS. The national ETS, a rate-based tradable performance standard, covers around 3,500 MT CO_2. We predict that the national ETS will increase China's climate patenting by around 5.46%.[21] China's national ETS only covers the power sector in the first stage. It will still overtake the EU ETS to become the world's largest carbon market. The national ETS would become a central policy instrument to achieve China's climate target by expanding the covered sectors. The experience from regional ETS pilots shows that even a relatively low carbon price can direct innovation toward low-carbon technologies, as long as the covered firms are cognizant that the ETS will be implemented and maintained in the long term.

This paper also sheds light on how firms adapt to carbon risk. As the major economies have committed to achieving carbon neutrality by the mid-century, carbon-intensive firms are facing increasing policy and regulatory risks in the transition to a low-carbon economy. Interestingly, the recent literature finds that the stocks of firms with higher carbon emissions are associated with higher returns, other things being equal (Bolton and Kacperczyk, 2020). Besides the interpretation that investors have already priced in the carbon risk, we provide an additional explanation that government interventions do not necessarily harm firms' financial performance. This finding aligns with the Porter hypothesis that appropriately designing environmental policies can enhance firm competitiveness (Porter and van der Linde, 1995). By engaging in climate innovation, firms can mitigate transition risks by saving inputs, improving energy efficiency, banking or selling excess carbon allowances, and henceforth turning carbon risk into profitable returns.[22]

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

[22] One possible channel that the climate innovator could achieve higher market returns is through its role in the carbon allowance market. Presumably, early-move innovators with better carbon mitigation technologies could decide to bank the excess carbon allowances when the carbon market expects to boom

7 Conclusion

This paper assesses the economic impacts of China's carbon ETS pilots on firms' innovation and financial performance. We compare climate patenting for regulated and unregulated firms using patent data on publicly listed firms and their subsidiaries. We find consistent and robust evidence supporting the directed technical change induced by the ETS. Using carbon price as a signal for regulatory stringency, we show that higher carbon prices create more incentives for climate patenting and increase innovation quality. In addition, we find no evidence that the ETS harms firm competitiveness. A further test on the role of innovation implies that climate innovation enables carbon-intensive firms to gain competitive advantages in profitability and productivity once the ETS comes into effect.

This paper leaves several venues for future study. First, we cannot provide a comprehensive picture of corporate climate mitigation pathways due to a lack of climate-related information at the firm level. The Chinese regulator does not require listed firms to disclose carbon emissions except for a few ones covered by the ETS. Second, quantity does not equal quality. We can only focus on the number of climate patents but do not have reliable information about their qualities. The Chinese patenting system does not provide essential quality indicators such as citations. Third, there is a gap in the literature documenting the climate and economic consequences of climate innovation. We need essential information about the effect of climate patents on carbon emissions reduction, as well as the R&D expenditure data, to understand firms' decisions on climate innovation better.

and reap profitable returns. To provide supporting evidence in this regard, detailed allowance transactions are expected. Unfortunately, this confidential information has not been revealed yet to academia.

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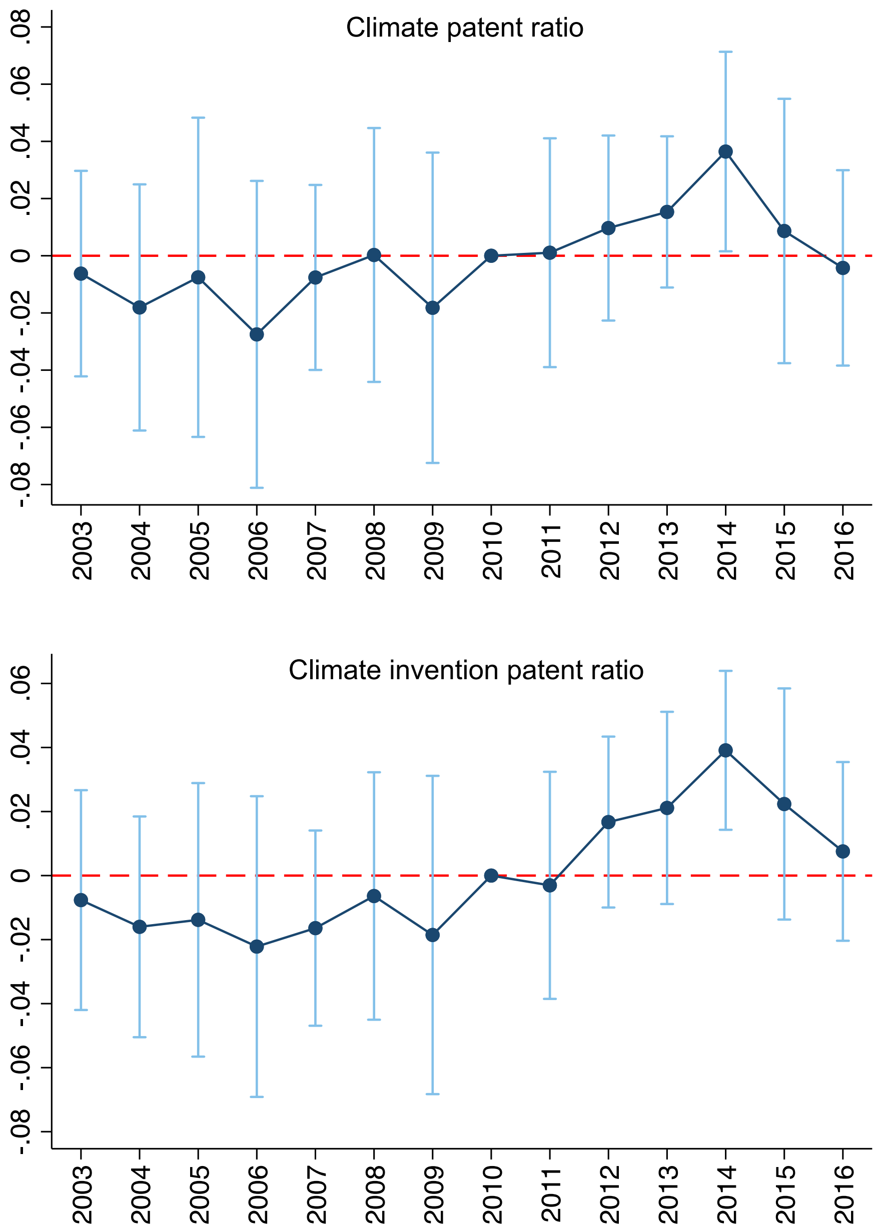

Figure 1: Dynamic Effects of the ETS on Climate Patenting

Notes: The upper panel illustrates the effects on the share of climate patents in all patents. The lower panel illustrates the effects on the share of climate patents in invention patents. Blue dots represent point estimates for the coefficients of time-specific indicators, while vertical lines indicate 95% confidence intervals. The regression results are based on Eq (3).

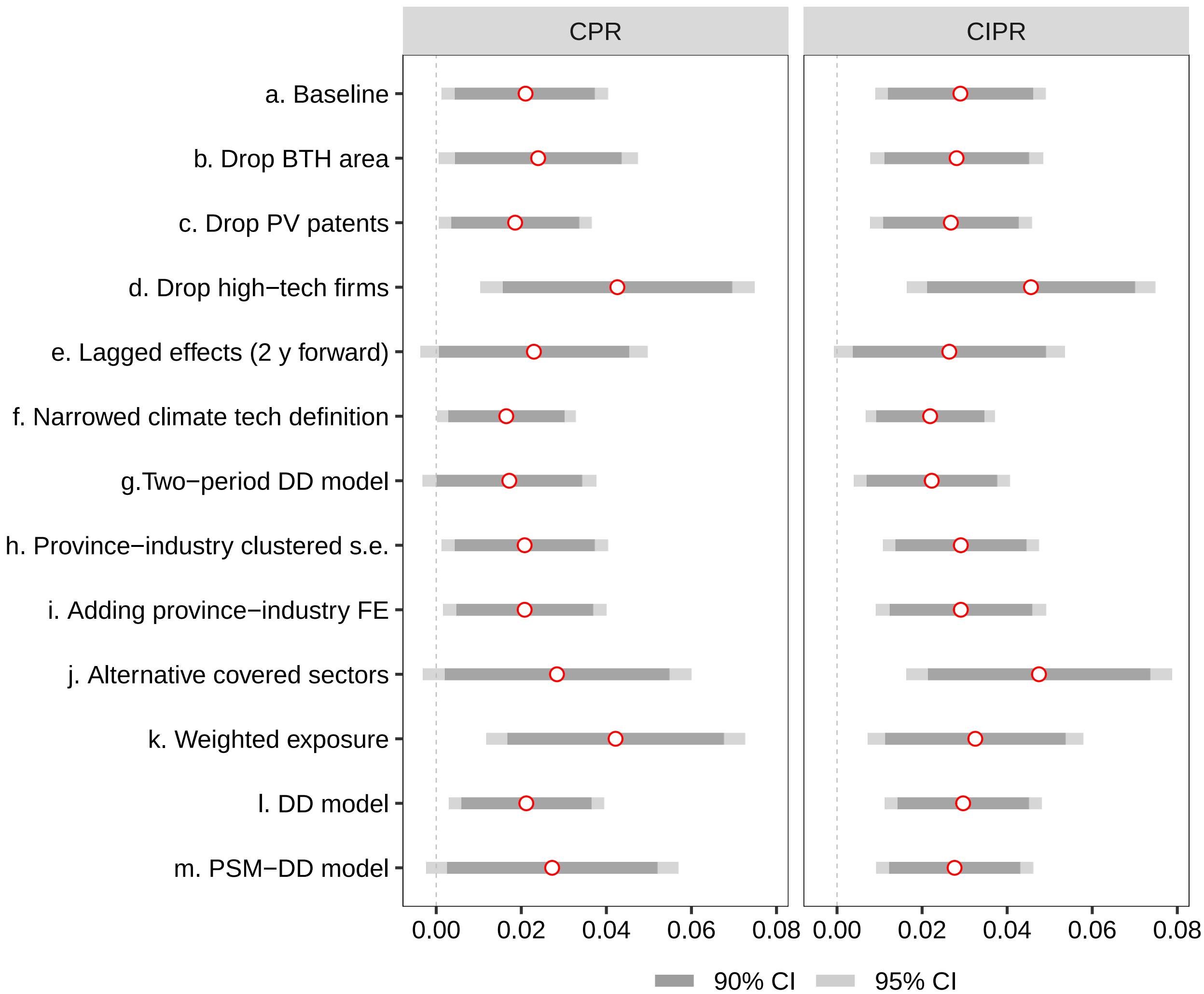

Figure 2: Robustness Checks of the Main Results

Notes: The left panel illustrates the ETS effects on the climate patent ratio (CPR). The right panel illustrates the ETS effects on the climate invention patent ratio (CPIR). Rows a to j are based on the baseline DDD model in Eq (1), Row k is based on the exposure model in Eq (4). Row l is based on a DD model, and Row m is based on a PSM model. Firm attributes include age, asset, capital, revenue, and operating cost. Fixed effects are included at firm, province-year, and industry-year levels. Standard errors presented in the parenthesis are clustered at the sector level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 1: Summary Statistics

VARIABLES	N	Mean	Std. Dev.		
			Overall	Betweeen	Within
	(1)	(2)	(3)	(4)	(5)
Panel A. Firm-level Patent Information					
Total patents	26,111	27.50	185.79	129.72	141.24
Invention patents	26,111	13.24	103.43	63.43	83.01
Climate patents	26,111	1.67	12.36	7.27	10.04
Climate invention patents	26,111	0.83	7.94	4.13	6.74
Climate patent ratio (CPR)	26,111	0.03	0.09	0.06	0.08
Climate invention patent ratio (CIPR)	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
Revenue (million Yuan)	25,497	6237.47	58333.49	48493.36	26585.60
Capital (million Yuan)	23,260	3088.96	21348.91	18548.04	7989.33
Wage (million Yuan)	25,487	395.57	2441.31	2023.22	1151.24
TFP-OP	21,626	3.51	0.73	0.62	0.37
TFP-LP	18,788	7.35	0.97	0.85	0.44
Panel C. Carbon Market					
Carbon price (Yuan/t-CO_2e)	26,111	3.28	11.28	6.13	9.72

Notes: The climate patent ratio is the share of climate patents in all patents. The climate invention patent ratio is the share of climate patents in invention patents. TFP-OP is measured by the Olley-Pakes method. TFP-LP is measured by the Levinsohn-Petrin method. Between/within standard deviation captures the variation between/within each listed firm.

Table 2: The Effects of the Carbon ETS on Climate Patenting

Dep. Var.	Climate patent ratio			Climate invention patent ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
ETS·Sector·$I(t \geq 2011)$	0.021**			0.029***		
	(0.010)			(0.010)		
ETS·Sector·$I(2011 \leq t \leq 2012)$		0.015**	0.019**		0.019**	0.020**
		(0.008)	(0.008)		(0.008)	(0.009)
ETS·Sector·$I(t \geq 2013)$		0.024**			0.034***	
		(0.011)			(0.012)	
ETS·Sector·$I(t \geq 2013)$·Price			0.010***			0.011***
			(0.003)			(0.003)
R-squared	0.092	0.093	0.093	0.094	0.094	0.095
Observations	21,531	21,531	21,531	21,531	21,531	21,531
Firm Attributes	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y

Notes: The dependent variable in columns (1)-(3) is the climate patent ratio, and the climate invention patent ratio in columns (4)-(6). Columns (1) and (4) follows the baseline DDD model in Eq (1); other columns are based on the two-period model in Eq (2). ETS is a dummy for pilot regions, Sector is a binary indicator for carbon-intensive sectors (i.e., covered sectors), $I()$ is a time index function, and Price is carbon allowance price. Firm attributes include age, asset, capital, revenue, and operating cost. A set of fixed effects at firm, province-year, and industry-year levels are included. Standard errors in parentheses are clustered at the sector level. Significance level: *** 1%, ** 5%, and * 10%.

Table 3: Estimation Results of the Corporate Regulatory Exposure Model

Dep. Var.	Climate patent ratio			Climate invention patent ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure$\cdot I(t \geq 2011)$	0.030***			0.023**		
	(0.011)			(0.010)		
Exposure$\cdot I(2011 \leq t \leq 2012)$		0.020**	0.016*		0.015*	0.011
		(0.009)	(0.008)		(0.009)	(0.009)
Exposure$\cdot I(t \geq 2013)$		0.036**			0.027**	
		(0.014)			(0.012)	
ExposurePrice$\cdot I(t \geq 2013)$			0.010**			0.007*
			(0.004)			(0.004)
R-squared	0.093	0.093	0.093	0.094	0.094	0.094
Observations	21,531	21,531	21,531	21,531	21,531	21,531
Firm Attributes	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y

Notes: The dependent variable in columns (1)-(3) is the climate patent ratio, and climate invention patent ratio in columns (4)-(6). Columns (1) and (4) follow the exposure model in Eq (4); other columns are based on the two-phase ETS exposure model in Eq (5). Exposure is defined in Eq (4), ExposurePrice is defined in Eq (5), $I()$ is a time index function, and Price is carbon allowance price. Firm attributes include age, asset, capital, revenue, and operating cost. A set of fixed effects at firm, province-year, and industry-year levels are included. Standard errors in parentheses are clustered at the sector level. Significance level: *** 1%, ** 5%, and * 10%.

Table 4: The ETS Effects on Firm Financial Performance

Dep. Var.	ROA (1)	ROE (2)	ROCE (3)	TFP-OP (4)	TFP-LP (5)
ETS·Sector·$I(t \geq 2011)$	0.008	0.029	0.042**	0.033	0.010
	(0.007)	(0.020)	(0.018)	(0.056)	(0.067)
R-squared	0.237	0.133	0.150	0.159	0.373
Observations	21,527	21,338	21,183	21,626	18,788
Firm attributes	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y

Notes: The dependent variables are ROA (return on assets), ROE (return on equity), and ROCE (return on capital employed). TFP-OP (TFP estimated by the Olley-Pake method) and TFP-LP (TFP estimated by the Levinsohn-Petrin method). ETS is a dummy for regional ETS pilots. Sector is a binary indicator for carbon-intensive sectors (i.e., covered sectors). $I(t \geq 2011)$ is a dummy for the year 2011 and after. Firm attributes include age, asset, capital, revenue, and operating cost. Standard errors in parentheses are clustered at the sector level. Significance level: *** 1%, ** 5%, and * 10%.

Table 5: The Effects of Climate Innovation on Firm Financial Performance

Dep. Var.	ROA		ROE		ROCE	
Regions	Non-ETS (1)	ETS (2)	Non-ETS (3)	ETS (4)	Non-ETS (5)	ETS (6)
Panel A: One-year Time Window						
Stock·Sector·$I(t \geq 2011)$	0.002	0.003	0.004	0.005	0.005	0.003
	(0.002)	(0.003)	(0.004)	(0.006)	(0.005)	(0.006)
Observations	1,997	897	1,997	897	1,997	897
R-squared	0.411	0.377	0.440	0.398	0.426	0.424
Panel B: Two-years Time Window						
Stock·Sector·$I(t \geq 2011)$	0.001	0.007***	-0.001	0.017**	-0.003	0.015*
	(0.003)	(0.002)	(0.006)	(0.007)	(0.009)	(0.008)
Observations	2,045	910	2,043	910	2,045	910
R-squared	0.309	0.320	0.174	0.235	0.280	0.265
Panel C: Three-years Time Window						
Stock·Sector·$I(t \geq 2011)$	-0.001	0.009***	-0.025	0.018**	-0.017	0.018**
	(0.003)	(0.004)	(0.017)	(0.009)	(0.011)	(0.009)
Observations	2,053	919	2,051	917	2,052	918
R-squared	0.269	0.288	0.190	0.241	0.232	0.266
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: The dependent variables are ROA (return on assets), ROE (return on equity), and ROCE (return on capital employed). Samples are divided by ETS regions and non-ETS regions. ETS is a dummy for regional ETS pilots. Sector is a binary indicator for carbon-intensive sectors (i.e., covered sectors). $I(t \geq 2011)$ is a dummy for the year 2011 and after. Stock is the time-invariant stock of climate patents before the ETS. Standard errors in parentheses are clustered at the sector level. Significance level: *** 1%, ** 5%, and * 10%.

Table 6: The Effects of Climate Innovation on Firm Productivity

Dep. Var.	TFP-OP		TFP-LP	
Regions	Non-ETS (1)	ETS (2)	Non-ETS (3)	ETS (4)
Panel A. One-year Time Window				
Stock·Sector·$I(t \geq 2011)$	0.001	0.025*	-0.001	-0.012
	(0.013)	(0.014)	(0.006)	(0.011)
Observations	1,905	848	1,561	688
R-squared	0.608	0.497	0.881	0.842
Panel B. Two-year Time Window				
Stock·Sector·$I(t \geq 2011)$	0.023	0.038*	-0.010	0.025**
	(0.017)	(0.021)	(0.019)	(0.011)
Observations	1,950	860	1,702	736
R-squared	0.469	0.388	0.714	0.691
Panel C. Three-year Time Window				
Stock·Sector·$I(t \geq 2011)$	0.022	0.047*	-0.010	0.058***
	(0.021)	(0.025)	(0.028)	(0.016)
Observations	1,954	865	1,719	751
R-squared	0.423	0.415	0.640	0.672
Firm Attributes	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y

Notes: Dependent variables: TFP-OP (TFP estimated by the Olley-Pake method) and TFP-LP (TFP estimated by the Levinsohn-Petrin method). Sector is a binary indicator for carbon-intensive sectors (i.e., covered sectors). $I(t \geq 2011)$ is a dummy for 2011 and after. Stock is the time-invariant stock of climate patents before the ETS. Standard errors in parentheses are clustered at the sector level. Significance level: *** 1%, ** 5%, and * 10%.

A Online Appendix

A.1 China's Regional ETS Pilots

China's seven regional ETS pilots regulate different 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% in Hubei to 60% in Tianjin.

Most pilots use benchmarking and grandfathering for allowance allocation, except 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%. Allowances are allocated annually, except for Shanghai, which allocated the allowances for the compliance period of 2013-2015 at one time. Allowances could only be 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 various 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 a rate-based tradable performance standard (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 (Goulder and Morgenstern, 2018; Pizer and Zhang, 2018; Goulder et al., 2019).[23] 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 (Fischer and Newell, 2008; Boom and Dijkstra, 2009).

A.2 Analysis of Sample Means

Table A2 shows a sample mean analysis for comparing climate patenting for the regulated and unregulated sectors. We start from columns (1)-(3), the result for the climate patent ratio. Panel A is the DD estimate of interest, in which we compare the shares of climate patents between the covered sectors in the pilots and the same sectors in the non-pilots before and after the ETS. The DD estimate suggests that ETS increases the climate patent ratio by 1.3 percentage points, significant at the 95% 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.

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 climate patent ratio by 1.6 percentage points. This statistically significant DDD estimate suggests that the regional ETS pilots direct sectoral innovation activities towards climate-friendly technologies. Furthermore, we conducted a similar analysis for the invention patents,

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

and the results are shown in columns (4)-(6) in Table A2. The conclusion is similar to the previous analysis.

A.3 Propensity Score Matching

A firm with at least one regulated parent or subsidiary is considered an ETS-regulated firm. We select similar unregulated firms as the comparison group for the regulated firms, conditional on their observable characteristics. With this restricted matched sample, we adopt a variant of the DD approach to examine the effect of ETS on climate patenting. The results are close to our baseline estimates. For each firm, the propensity score is calculated based on its pre-ETS financial indicators (i.e., total assets, capital, and revenue in two years before the ETS) and innovation indicators (i.e., accumulative levels of total and climate patenting activities in one year before the ETS). There is a lack of consensus on which variables should be included for calculating propensity scores. A large number of restrictions and variables, while deemed stringent and safe, tend to cause fewer matched pairs. Thus, we choose variables strongly correlated with the outcomes to 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 can 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 and control groups. Online Appendix Table A4 provides the balancing test. In columns (1) - (3), we observe substantial differences in firm financial and innovation attributes between the treated and control groups in the unmatched sample. In columns (4) - (6), the statistical differences in these firm attributes disappear in the matched sample. These findings suggest that the matching procedure performs well in obtaining control units comparable to regulated firms.

A.4 Placebo Test

We consider the water pollution-intensive sector as the pseudo-covered sector while assuming the water pollution-saving patent ratio 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 A5 in the Online Appendix. As expected, we find no statistically significant effect of ETS on patenting not related to climate technologies. It suggests that the ETS, rather than other environmental policies, drives climate innovation.

A.5 Innovation Quality

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).[24] To this end, we retrieve future patent citations associated with all climate patent applications from the Google Patent Project from 2010 to 2017.[25] Using the climate innovation quality as an alternative measure, columns (1) and (2) in Table A6 in the Appendix provide the corresponding results. Panel A refers to the baseline DDD model, Panel B considers listed firms' exposure to ETS, Panel C separates the ETS effect into two phases while accounting for the carbon price of Phase II, and Panel D further incorporates the corporate exposure to ETS and carbon price in Phase II. Similar to the baseline results, these estimates highlight the ETS effect mainly occurring in Phase II: allowance trading and price play a substantial role in improving the quality of climate patenting.

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

[25] 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.

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 (3) and (4) of Table A6 separate the DDD estimate in column (1) of Table 2 by patent types. Both estimates are positive, but only the estimate for the invention patents is statistically significant at the 5% level. It suggests that ETS stimulates more high-quality innovation embodied by invention patents instead of marginal innovation represented by utility model patents.

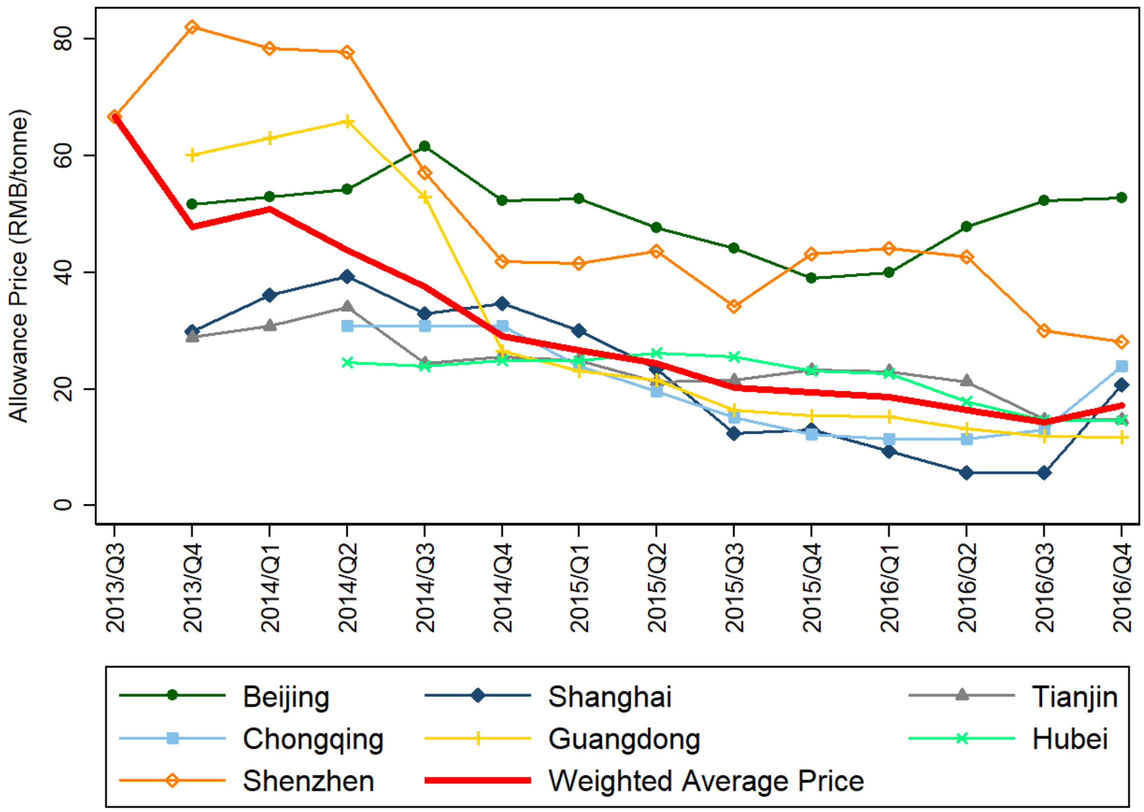

Figure A1: Carbon Prices across Regional Pilots

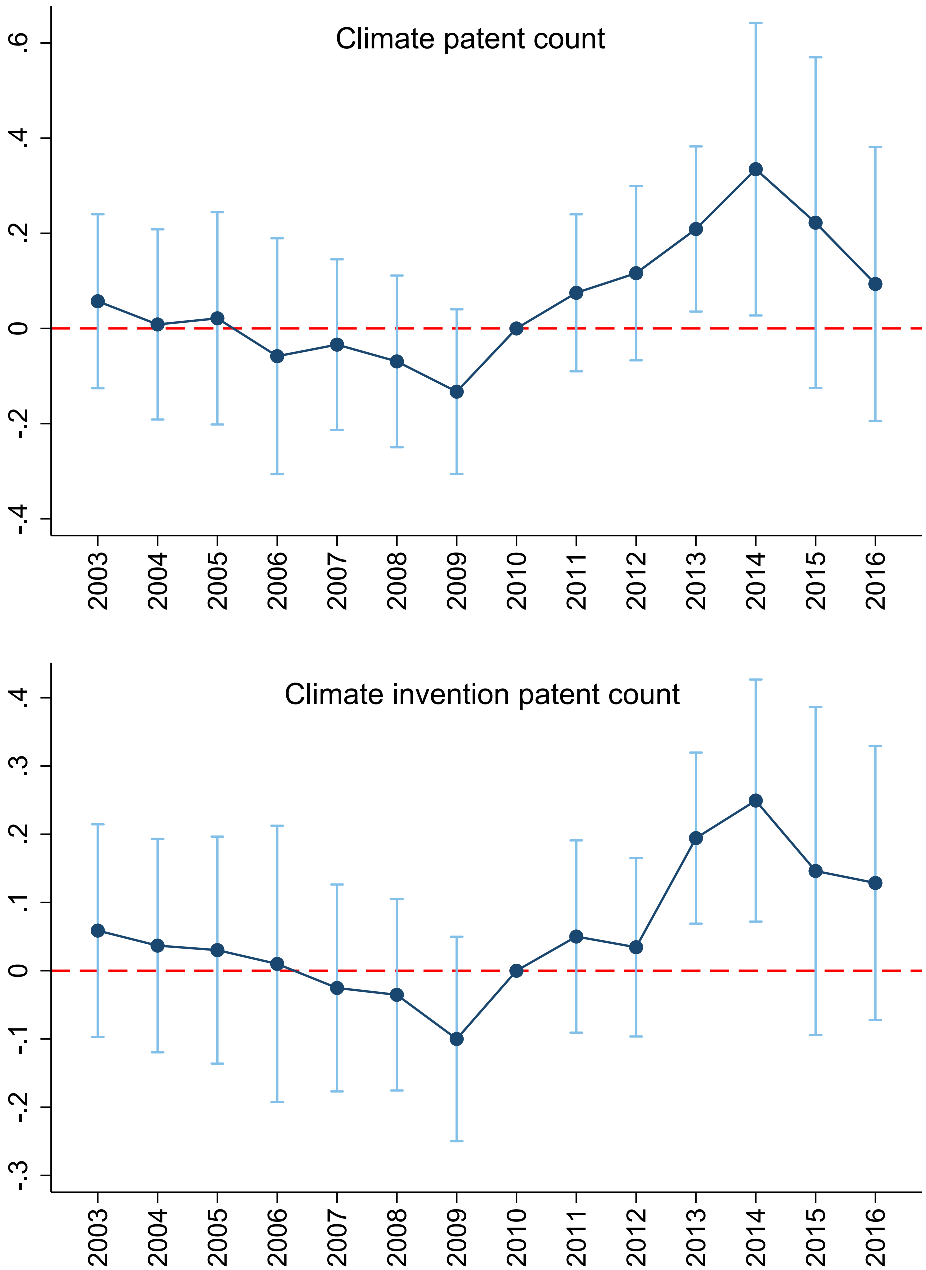

Figure A2: Dynamic Effect for Climate Patent Count

Notes: Charts from up to down show the dynamic impacts of ETS on climate patent count and climate invention 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 model Eq (3) is conducted for firms' innovation outcomes.

Table A1: Summary of Covered Sectors across Pilots

Region	Announce 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, textile, 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, paper making	Energy consumption >60k tce	33%
Shanghai	2011	2013	510Mt (3 years)	Free allocation	Electricity, iron and steel, petrochemical and chemical industries, metallurgy, building materials, paper making, textile, 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 building >10k m^2	40%
Tianjin	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: The DDD Estimate of the ETS Effect Using Sample Means

	Climate patent ratio			Climate invention patent ratio		
	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 A3: Baseline Regression Results for the ETS Effect on Climate Innovation

	(1)	(2)	(3)	(4)	(5)
Panel A. Dependent Variable: Climate Patent Ratio					
ETS·Sector·$I(t \geq 2011)$	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: Climate Invention Patent Ratio					
ETS·Sector·$I(t \geq 2011)$	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
Panel C. Dependent Variable: Climate Patents					
ETS·Sector·$I(t \geq 2011)$	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 D. Dependent Variable: Climate Invention Patents					
ETS·Sector·$I(t \geq 2011)$	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 model Eq (1). ETS is a dummy for regional ETS pilots, Sector is a binary indicator for carbon-intensive sectors (i.e., covered sectors), and $I(t \geq 2011)$ is a dummy for the year 2011 and after. The firm attributes include age, asset, capital, revenue, and operating cost. The firm, province-year, and industry-year fixed effects are included. Standard errors in parenthesis are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A4: Robustness Check: Balancing Test for Regulated and Unregulated Firms

	Unmatched Sample 207 treated vs 2,022 control			Matched Sample 134 treated vs 123 control		
Var.	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
Climate patent	0.860	0.354	0.000	0.752	0.641	0.411
Climate patent stock	1.513	0.724	0.000	1.372	1.280	0.619

Notes: For each firm, the propensity score is calculated based on its pre-ETS financial indicators (i.e., total assets, capital, and revenue in two years before the ETS) and innovation indicators (i.e., accumulative levels of total and climate patenting activities in one year before the ETS). All covariates are log-transformed. Replacement is allowed in the matching procedure.

Table A5: Placebo Test: Water Pollution

Dep. Var.	Water pollution control patent ratio		Non-climate patent ratio	
	(1)	(2)	(3)	(4)
ETS·$\text{Water}_1 \cdot I(t \geq 2011)$	-0.003		-0.024	
	(0.002)		(0.067)	
ETS·$\text{Water}_2 \cdot I(t \geq 2011)$		0.002		-0.016
		(0.005)		(0.032)
R-squared	0.101	0.101	0.268	0.268
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: ETS is a binary indicator for the pilot regions. The indicator function $I(t \geq 2011)$ is one for the year 2011 and after. Water_1 and Water_2 are two alternative binary indicators for water-pollution-intensive sectors. The former is defined by Cai, Chen, and Gong (2016), while the latter is reported by the Census of Pollution Statistics Survey. Firm attributes include firm age, asset, capital, revenue, and operating cost. The firm, province-year, and industry-year fixed effects are included. Standard errors presented in the parenthesis are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A6: The ETS Impacts on Innovation Quality

Dep. Var.	Climate patents weighted by citations (1)	Climate invention patents weighted by citations (2)	Share of climate invention patents in all patents (3)	Share of climate utility patents in all patents (4)
Panel A. Baseline DDD model				
ETS·Sector·$I(t \geq 2011)$	0.171	0.111	0.012**	0.009
	(0.116)	(0.088)	(0.005)	(0.006)
R-squared	0.249	0.198	0.083	0.086
Panel B. Baseline DDD Model and Carbon Price				
ETS· Sector·$I(2011 \leq t \leq 2012)$	0.135	0.062	0.004	0.015**
	(0.114)	(0.082)	(0.005)	(0.007)
ETS· Sector·$I(t \geq 2013)$·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. Corporate Exposure to ETS				
Exposure·$I(t \geq 2011)$	0.148*	0.111*	0.013***	0.017**
	(0.080)	(0.060)	(0.005)	(0.008)
R-squared	0.249	0.198	0.083	0.086
Panel D. Corporate Exposure to ETS and Carbon Price				
Exposure·$I(2011 \leq t \leq 2012)$	0.013	-0.001	0.006	0.010
	(0.093)	(0.075)	(0.004)	(0.006)
ExposurePrice·$I(t \geq 2013)$	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

Notes: Panels A, B, C, and D, refer to the baseline DDD model Eq (1), baseline DDD and carbon price model Eq (2), corporate exposure model Eq (4), and corporate exposure and carbon price model Eq (5), respectively. Price denotes carbon price for regional ETS pilots. The firm attributes include age, asset, capital, revenue, and operating cost. The firm, province-year, and industry-year fixed effects are included. Standard errors presented in the parenthesis are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.