# The impact of carbon emission trading policy on firms' green innovation in China

Hongxin Yu[1], Yaohui Jiang[2], Zhaowen Zhang[2], Wen-Long Shang[3,6,7*] , Chunjia Han[4] and Yuanjun Zhao[5]

*Correspondence:
shangwl_imperial@bjut.
edu.cn
[3] College of Metropolitan
Transportation, Beijing
University of Technology,
Beijing 100124, China
Full list of author information
is available at the end of the
article

## Abstract

This study aims to examine the green innovation effect of the carbon emissions pilot policy in China. First, using the difference-in-differences method and regressions of instrumental variables using the data from Chinese listed firms, we verify that the policy promotes green innovation among regulated firms and is more pronounced among state-owned enterprises, firms in the eastern region, and those with lower financing constraints. Furthermore, this positive effect spreads downstream relative to the regulated firms through input–output linkages, but reduces green innovation to upstream firms. Accordingly, such diffusion of innovation is achieved through the price mechanism. The results necessitate the introduction of various derivatives to mobilize the market to reduce the speculative volatility of carbon prices. In addition, relevant supporting policies must be established to encourage corporate innovation to reduce the crowding-out effect owing to emission reduction and the nonmarket factors.

**Keywords:** Carbon emission, Carbon finance innovation, Green innovation, Environmental regulation, Differences-in-differences

## Introduction

The issue of carbon dioxide emission is interrelated to the sustainable development of mankind, and all countries in the world are adopting environmental regulations (Elahi et al. 2022a, b; Yang et al. 2022) to prevent or reduce its effect on climate change and ecosystem disruption (Elahi et al. 2021; Liu et al. 2022). In 2011, the National Development and Reform Commission of China issued a "Notice on Carrying out the Pilot Work of Carbon Emission Trading,[1]" which launched the pilot carbon emission trading in seven provinces (cities), with the aim to promote economic development while reducing carbon dioxide emission. This move stimulated academic discussions on the environmental effect of China's carbon emission policy, which demonstrated its positive influence on the transformation of China's energy structure while achieving emission reductions (Hu et al. 2020a; Tang et al. 2021; Zhang et al. 2020). High-carbon fossil energy combustion is not only the primary source of greenhouse gases but also produces particulate matter, sulfur, and nitrogen oxides, which are the main sources of the current

---

[1] For details of the document, see the official website of the National Development and Reform Commission: https://zfxxgk.ndrc.gov.cn/web/iteminfo.jsp?id=1349.

Yu *et al. Financial Innovation*      (2022) 8:55

Page 2 of 24

air pollution. In addition to being harmful to human health, air pollution is related to residents' happiness and regional crime rate, which are all closely associated with people's quality of life (Bondy et al. 2020; Zhang et al. 2017). Given the negative impact of carbon emissions, its reduction has gained scholarly attention. Compared with the emission reduction on the consumer side (Wang et al. 2021; Bi et al. 2022, 2021; Shang et al. 2021), that at the production side has received greater attention, among which carbon emission trading is an important method. As opposed to a blanket carbon tax on all companies, the carbon market allows companies to freely decide the best means to fulfill their emission reduction obligations. The policy achieved the total industry control target for the year while using market mechanisms to compress the marginal cost of internal innovation and emissions reduction, achieving a win–win situation for both the society and environment.

Unlike intangible assets with long life and illiquidity, carbon allowances for trading are incorporated into enterprise financial asset accounts. However, China's carbon emissions trading is primarily spot trading, with low financialization and carbon monetization, manifested by limited channels for carbon financial products and services and a lack of carbon financial derivatives trading mechanism (Zhang and An 2014; Huang et al. 2021). A sound financial system reduces the financing constraints of market participants, allows full utilization of the price mechanism, and promotes economic growth (Panizza 2012). Innovation in finance supports and promotes that of enterprises through funding (He and Tian 2018). The particularity of carbon emission rights as a financial asset reflects derivative financial attributes, specifically the market behavior of using funds leverage to promote market flow (Haas and Popov 2018). Carbon emissions trading closely connects the financial capital and the low-carbon real economy (Jiang et al. 2012). On the one hand, financial capital is directly or indirectly invested in energy-saving and emission-reducing enterprises and projects. On the other hand, the generated carbon emission reductions by such enterprises and projects enter the carbon financial market for trading, and are developed into carbon financial spot and derivatives. Can these promote the green innovation of regulated enterprise? Can these drive the green innovation of upstream and downstream related company? Relatively few studies address these issues, which are the purpose and content of the current study.

The remainder of the paper is organized as follows: "Literature review" section discusses the literature review. "Hypothesis" section provides the policy background and theoretical hypotheses.  "Data and model description" section describes the model and data sources. "Results and Network conduction effect" section discuss the empirical analysis of the policy effect on innovation in the regulated industry and verify its diffusion and transmission mechanism, respectively. "Conclusions and suggestions" section presents the study conclusions and suggestions.

## Literature review

### Influence on regulating enterprise innovation

Positive and negative views have been presented regarding the effect of carbon emissions trading policies on corporate green innovation. On the one hand, the cost and operational constraints owing to policy restrictions on capacity depletes the firms' R&D investment and ultimately hinder their innovation (Chen et al. 2021a, b). Essentially,

regulatory policies such as carbon emission rights trading use legal or administrative measures to formulate stricter pollution emission standards and equipment iteration requirements and other measures to limit the backward production capacity of regulated companies. Greenstone (2002) analyzed the impact of the clean air law in the United States on regulated companies. Compared with regions that meet regulatory standards, noncompliant regions lost approximately 590,000 jobs, \$37 billion in capital stock, and \$75 billion in output owing to stricter environmental regulations. Enterprises affected by the policy face difficulties in re-optimizing the resource allocation in a short time period, breaking the capital chain and causing loss of skilled workers. The mismatch of capital, labor, and other production factors ultimately inhibit corporate green innovation. Conversely, carbon trading policies are also said to promote green innovation in regulated companies, which use advanced equipment for clean production to meet carbon emission limits and resell excess emission rights in the secondary market to companies with higher marginal costs. Therefore, the policy strengthens the innovation motivation of enterprises, reduces the marginal costs of emission reduction, and eases the cost constraints caused by emission reduction (Montero 1998). Carbon financial innovation can better facilitate the discovery and stabilization of carbon prices to serve related emissions trading activities, which improves the investment atmosphere, stabilizes uncertainty, and promotes green innovation in the market.

In particular, China's carbon emissions trading pilot policy has received widespread scholarly attention for its innovative effects owing to its considerable emission reduction potential (Liu et al. 2017). However, empirical studies do not form a unified opinion owing to their different sample intervals, granularity, and innovation indicators. Most scholars who use regional panel data to analyze this issue believe that the innovation effect of the policy has not yet emerged. The reason is that the current Chinese carbon market is still in its development stage, and the lagging legislation and imperfect trading mechanism ultimately prevent enterprises from reducing the cost of green innovation through the carbon market (Feng et al. 2019; Chen et al. 2021a, b; Du et al. 2021; Liu et al. 2021). To examine the net impact of the policy, the aforementioned scholars set pilot regions as the experimental group and the other regions as the control group. Given the limitation of sample granularity, this result only reflects the average effect of the policy in one place and leads to difficulties in identifying its heterogeneous impact (Shang et al. 2020; Yu 2022). To further examine the micro-level mechanism of the policy, scholars also analyze a sample of listed companies, generally in the regulated industries in the pilot regions, as the experimental group. The empirical evidence reveals that the policy promotes the enterprise innovation in regulated industries, among which the innovation effects of state-owned and large-scale enterprises are stronger than on other sectors (Hu et al. 2020b; Zhang et al. 2019; Yu et al. 2021). In constructing the econometric model, difference-in-differences (DID) and its derivative models are commonly used to discuss the effect of policy on innovation (Liu and Sun 2021). This approach originates from the "credibility revolution" in econometrics, where randomized experiments are simulated by available observations to avoid spurious regressions owing to endogeneity, thereby enabling the transition from correlation to causation (Angrist and Pischke 2010). The net effect is decomposed by comparing the innovation changes before and after the policy shock in the experimental and control groups, and therefore, the precise

identification and splitting of the two groups is the key to the effectiveness of the double difference model. Objectively, each pilot region has set different entry thresholds, and not all its enterprises in regulated industries are included in the carbon market. If the micro-objects of the policy are not accurately identified, the self-selection problem may lead to biased conclusions. Therefore, the ability to effectively identify the list of trading companies published in each regional carbon market is crucial to obtain robust samples and credible conclusions.

**Innovation spillover effects of the policy**

Although carbon emission rights trading acts on specific companies in regulated industries, its innovative effects may spread to other industries or regions. Extant literature mostly analyzes its effects from the perspective of spatial correlation (Du et al. 2021; Yu and Li 2021; Gao et al. 2021). Although the spatial weight matrix can effectively measure the correlation between regions, accurately determining the specific paths and mechanisms of spillover effects is difficult. Furthermore, the introduction of production networks provides a new perspective for this study. First developed by macroeconomists, this concept considers production networks an important channel that links macroeconomic fluctuations and micro-individual decisions (Acemoglu et al. 2012b). Rostas and Leontief (1952) found that "the presence of these invisible but nevertheless very real ties can be observed whenever expanded automobile sales in New York City increase the demand for groceries in Detroit, or when the sudden shutdown of the Pennsylvania coal mines paralyzes the textile mills in New England." The objective input–output linkages between these different industries constitute the production network (Carvalho and Tahbaz-Salehi 2019). On this topic, current research mainly comprises two directions. First, based on macroeconomic fluctuations and general equilibrium theory, numerical simulations are used to analyze the heterogeneous effects of different shocks on the industry (Acemoglu et al. 2016; Liu 2019). Second, the spillover effects of specific exogenous shocks on upstream and downstream related companies are discussed. Carvalho et al. (2020) examined the economic fluctuations triggered by the 2011 earthquake of the Pacific coast of Tohoku, in which the decline in output value in directly affected areas accounted for 0.15% of Japan's gross domestic product (GDP) loss. However, the actual GDP decline that year was 0.8%, empirically suggesting that the breaks in industrial chain were the core cause of the greater economic losses. Demirgüç-Kunt et al. (2020) investigated the adjustment of the Resource Utilization Support Fund tax for domestic importers in Turkey, and the reform-induced cost constraints are similarly transmitted to downstream suppliers.

In summary, this study presents three contributions. First, China became the world's largest carbon market in 2021, covering more than four billion tons of carbon dioxide emissions. The effects were evident not only on regulated industries but also on upstream wind power, midstream electric furnace steelmaking, and downstream new energy vehicles, all of which are likely to benefit from carbon trading. Therefore, this study investigates the innovation spillover effects of carbon emissions trading from the perspective of production networks to precisely identify the heterogeneous effects of policies on upstream and downstream enterprises, provide new ideas for assessing the costs and benefits of policies, and further explore the micro-action paths through

**Table 1** Pilot provinces (cities) and start-up times of their carbon emission trading

| Pilot provinces (cities) | Start-up time |
|---|---|
| Shenzhen | 2013-6 |
| Beijing | 2013-11 |
| Shanghai | 2013-11 |
| Guangdong | 2013-12 |
| Tianjin | 2013-12 |
| Hubei | 2014-2 |
| Chongqing | 2014-6 |
| Fujian | 2016-9 |

subsample regressions and mechanism tests, which have certain implications for the subsequent construction of carbon markets in developing countries. Second, this study matches the data of listed companies and their subsidiaries based on the published list in each regional carbon market. Compared with regional panel data, this list of regulated firms can more intuitively reflect the impact on innovation, providing data support for further exploring the micro mechanisms of direct and spillover effects. Finally, a multi-angle robustness test is conducted to comprehensively analyze the effects of policies. Considering the situation that endogeneity and missing variables lead to biased results (Becker et al. 2020; Li et al. 2021; Chen et al. 2021a, b), methods such as propensity score matching (PSM) and instrumental variables (IV) for robustness analysis are conducted before the regression analysis of the DID model.

## Hypothesis
### Policy implementation
China's economic growth and energy consumption present a certain imbalance (Zhao et al. 2020). Since 2005, China's total carbon emission has been the largest in the world (Cai et al. 2019; Liu and Lin 2018). Facing the pressure of domestic transformation and international climate governance, the Chinese government has actively enacted carbon emission measures, which mainly includes the following three stages.

Initial exploration (2002–2013). The "Kyoto Protocol" signed by China in 2002 formally came into effect during this period. In 2004, the "Interim Measures for the Operation and Management of Clean Development Mechanism Projects" was promulgated aiming to achieve a win–win situation through project-level emission reduction transactions with contracting states. Developed countries have heavy emission reduction tasks and high marginal costs and need to purchase emission reductions from developing countries to increase their utility. In turn, developing countries can obtain financial support while achieving environmental improvements. However, the scale and effect of carbon emission reduction are relatively limited owing to the error between the actual measurement of emission reduction and the expectation, large initial capital investment, long payback period, and unpredictable fluctuations of the carbon trading market.

Pilot reform (2014–2020). In 2014, China's National Development and Reform Commission officially approved seven provinces (cities) to launch carbon emission trading. Table 1 presents the specific pilot provinces and their start-up times. In these pilots, the upper

limit of total emissions are set based on their own carbon dioxide emissions, and quotas of each company are set in accordance with the historical or benchmark emissions of the regulated company (Shang et al. 2022). Compared with the one-size-fits-all carbon tax, the advantage of carbon emission rights lies in the controllability of total emission reduction, allowing companies to reduce its related costs through market mechanism. However, the design, monitoring, reporting, and verification of transactions are more complicated. If a company's carbon dioxide emission surpasses the limit, then the company not only needs to pay but also receives a fine of 1–5 times the average carbon market price of the year, credit investigation, and double deduction from the quota for the following year.

Full-scale rollout period (2021 and onwards). In June 2021, China's power industry carbon emission trading market was established. Covering 2225 companies in the power industry, a unified national carbon market covers more than four billion tons of emission, making it the largest in the world for greenhouse gas emission. Future policy is expected to further cover multiple high-emission industries. Compared to the pilot period, the expansion of carbon emission trading level is expected to increase the breadth and depth of the production network transmission. Companies in new energy supply and transportation, steel and cement preparation, new energy vehicles, and many other industries may benefit from carbon trading.

### Theory and hypothesis

If the benefit of extra production exceeds the cost, the company continues to produce. Such costs comprise three types, namely, innovation (green technology or equipment research and development (R&D) costs), transactions of carbon market purchases, and excess emission costs owing to repayment. The assumption is that financial services are relatively complete and the carbon emissions trading market is sound. Accordingly, three types of carbon emission regulated companies are assumed in the pilot provinces: buyers purchasing carbon allowance, sellers trading carbon allowance, and companies outside of carbon emission trading. The third type has likely achieved their emission reduction targets by introducing clean equipment or energy-saving innovations. As for the buyers, purchasing carbon allowance through the carbon trading market has lower costs than R&D. Meanwhile, the seller realizes energy-saving innovation at a lower cost. For instance, if the marginal benefit of increasing production is less than that of transferring carbon emission rights, then these additional rights are sold on the market. With price fluctuations in the carbon emissions trading, the three types of enterprises realize a mutual transformation. While achieving its relevant target, the market reduces its industry emission reduction costs, ultimately achieving a win–win situation. Accordingly, we propose Hypothesis 1.

**Hypothesis 1**  The emission trading policy increases the production costs of regulated companies and promotes its green innovation by reversing the mechanism and market incentive.

From the perspective of the production network, the policy affects the upstream and downstream enterprises (Baqaee and Farhi 2019; Li et al. 2020). The policy internalizes the negative externality of carbon emissions, reduces the production capacity of regulated companies, increases the industry production costs, and ultimately

hinders the innovation of upstream companies. In particular, capacity compression reduces the demand for upstream industrial products, for which the unit cost of upstream enterprise innovation increases. The policy affects the original production and operation order of enterprises, and the excess capacity of upstream enterprises is difficult to release in the short term. Therefore, market friction and resource misallocation problems arise, additional costs are generated, and innovation investments are depleted. However, facing a smaller product market in the future, enterprises expect that the innovation costs can only be shared by less output. Thus, the innovation cost per unit product increases, which simultaneously reduces green innovation. Accordingly, we propose Hypothesis 2.

**Hypothesis 2**   The emission trading policy increases the operating costs and hinders the green innovation of upstream companies.

Cost constraints bring a reversing mechanism. The increase in production costs of regulated industries are transferred downstream through product price. The increase in costs of upstream raw materials then forces downstream companies to reduce cost constraints through innovation or introduction of new technologies (Acemoglu et al. 2012a; Wu et al. 2022a, 2022b; Zheng et al. 2021). In particular, the carbon emission trading policy leads to an increase in the production costs of the regulated industry, which in turn raises their product prices. Simultaneously raising their production costs, downstream industries are forced to upgrade innovation to alleviate such impact. Subsequently, innovations in the regulated industry trigger a spillover effect. Concurrently, the energy-saving innovation of regulated companies is accompanied by new processes and improvements of product quality (Liu 2019). The overflow of innovation promotes the innovative development of the downstream industry. Accordingly, we propose Hypothesis 3.

**Hypothesis 3**   The emission trading policy promotes green innovation of downstream enterprises through the reversal mechanism and innovation transmission.

## Data and model description

### Samples and data sources

The data of listed companies on the A-share main board of the Shanghai and Shenzhen stock exchanges from 2009 to 2019 are taken as the initial sample for preliminary screening. However, the following companies are excluded: prefixed with ST, *ST, and PT, which represent loss in the continuous fiscal year; financial and insurance; have numerous missing values; and those in Fujian province, which constitute the second batch of carbon emissions trading pilots. The Fujian pilot implementation is relatively short and including it in the study may affect the effectiveness of evaluation. To ensure the robustness of the conclusion, we extend the time range of the sample as much as possible. Given the availability and quality of data, only those from 2009 to 2019 are usable. The sample data are derived from the CSMAR and the Wind databases, and green patent data are supplemented by the CNRDS database.

Yu *et al. Financial Innovation*     (2022) 8:55

Page 8 of 24

### Empirical model and variable definition

#### Benchmark model and variable definition

This study constructs a DID model to examine the direct effect of the carbon trading policy. The benchmark model is set as follows:

$$Gpatent_{it} = \beta_0 + \beta_1 Treat_i \times Time_t + \beta_2 Control_{it} + \mu_i + \sigma_t + \varepsilon_{it}. \tag{1}$$

$Gpatent_{it}$ represents the green patent level of company $i$ in period $t$. $Treat_i$ denotes the variable for grouping enterprises, set to 1 for regulated company and 0 for nonregulated company. $Time_t$ is a period grouping variable, set to 1 on and after 2014 and set to 0 before 2014. In certain pilot areas, the policy is implemented from the middle to the end of 2013. Considering the small number of carbon emission trading in 2013, the impact of the policy in 2013 is limited, and this study considers 2014 the starting time of the policy. $Control_{it}$ indicates the variable at the enterprise level, $\mu_i$ represents the firm fixed effect, $\delta_t$ denotes the time fixed effect, and $\varepsilon_{it}$ represents the residual term. $\beta_0$ is a constant term; $\beta_1$ represents the direct effect of the carbon emissions trading policy on the green innovation of a regulated company; and $\beta_2$ is the influence coefficient of other variables on the green innovation of regulated enterprise.

1. *Explained variable*: Green innovation level. For this factor, the proxy variables in the model and robustness tests are the natural logarithms of the number of green invention patents and of green utility model patents applied by listed companies. Given their high requirements for innovation, green invention patents are difficult to obtain and can effectively represent the innovation level of enterprises. In addition, the patent approval takes time. Compared with the number of granted patents, the number of applied patents can directly reflect the level of green enterprise innovation. We match patent data applied by all listed companies according to the list of international green patents issued by the State Intellectual Property Office of China to calculate the proxy variable data.

2. *Core explanatory variable*: Crossover between the regulated company and implementation time of the policy. We manually compile the list of the first batch of companies that participate in carbon emissions trading, matching the names of the listed parent companies and their subsidiaries. The matching method can more precisely identify the regulated companies. If the enterprise is not in the pilot area, but its subsidiary is included in the list of controlled companies, then it is considered a regulated company.

3. *Control variables for the company*: (1) Age (*Age*) is calculated by subtracting the year of establishment from the current year (unit: year) and natural logarithm processing; (2) Size (*Scale*) is the total assets in the current year (unit: yuan) and natural logarithm processing; (3) Asset–liability ratio (*Dar*) is the liabilities divided by total assets (unit: percentage), which reflects their debt management; (4) Return of earnings (*Roe*) is the profit divided by total assets (unit: percentage), which reflects profitability; (5) Total asset turnover (*Tat*) is the total sales revenue divided by total assets (unit: percentage), which reflects the ability of the company's capital to obtain their net income; (6) Current ratio (*Cr*) is the current assets divided by all current liabilities (unit: percentage), which reflects the ability to pay short-term debts; (7) Quick

Yu *et al. Financial Innovation*    (2022) 8:55

Page 9 of 24

**Table 2** Calculation methods and descriptive statistics of variables

| Variable | Calculation method | Observations | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| *Gpatent* | ln(number of green invention patent applications) | 26,002 | 0.512 | 0.941 | 0 | 7.224 |
| *Age* | ln(company age) | 25,997 | 2.821 | 0.354 | 1.610 | 3.466 |
| *Scale* | ln(company size) | 25,702 | 22.096 | 1.314 | 19.296 | 26.069 |
| *Dar* | Company total liabilities/total assets | 25,702 | 0.447 | 0.217 | 0.054 | 0.987 |
| *Roe* | Company net profit/net assets | 25,458 | 0.060 | 0.145 | − 0.787 | 0.376 |
| *Tat* | Company sales revenue/total assets | 25,701 | 0.647 | 0.457 | 0.047 | 2.639 |
| *Cr* | Company total current assets/total current liabilities | 25,702 | 2.375 | 2.656 | 0.187 | 17.805 |
| *Qr* | Company total quick assets/total current liabilities | 25,702 | 1.906 | 2.449 | 0.125 | 16.371 |
| *Mfr* | Company management expenses/main business income | 25,698 | 0.102 | 0.101 | 0.009 | 0.713 |

ratio (*Qr*) is referred to total quick assets divided by total current liabilities (unit: percentage), which reflects the ability of the company's cash or immediately realizable assets to repay current liabilities; (8) Management expense ratio (*Mfr*) denotes expenses divided by main business income (unit: percentage), which reflects the management level of enterprises. Table 2 reports the statistical characteristics and calculation methods of the main variables.

### *Two-stage model and instrumental variable*

Policy shock objectively weakens the endogenous problem owing to bidirectional causality, but missing variables may remain and cause a biased regression. To alleviate this possible endogenous problem, we introduce the city-level ventilation coefficient in the year before the policy implementation as the instrument variable. The two-stage instrumental variable model is expressed as follows:

$$Treat_i \times Time_t = \alpha_0 + \alpha_1 IV_i + \alpha_2 Control_{it} + \dot{\mu}_i + \dot{\sigma}_t + \dot{\varepsilon}_{it}, \tag{2}$$

$$Gpatent_{it} = \beta_0 + \beta_1 \widehat{Treat_i \times Time_t} + \beta_2 Control_{it} + \mu_i + \sigma_t + \varepsilon_{it}. \tag{3}$$

In the aforementioned equations, $IV_i$ represents the instrumental variable at the city level and $\widehat{Treat_i \times Time_t}$ is the predictive value of $Treat_i \times Time_t$. The selection of instrument variable must meet the exogeneity requirements, and the ventilation coefficient, as a natural condition, does not directly act on the green innovation level of the enterprise. From the perspective of correlation, the dilution capacity of pollution is stronger in areas with large ventilation coefficient, and the environmental pollution problem caused by high energy consumption is relatively less prominent. Therefore, the pilot provinces prioritize areas with low ventilation coefficient and relatively prominent pollution, which may have a negative relationship. The ventilation coefficient is calculated as follows:

$$Vc_i = \sum\nolimits_{m=1}^{m=12} Wh10_{im} \times Blh_{im}/12. \tag{4}$$

In the aforementioned equation, $Vc_i$ indicates the ventilation coefficient; $Wh10_{im}$ is the wind speed at 10 m; $Blh_{im}$ is the boundary layer height; $m$ denotes the month; and $i$ is the location of the company. The re-analysis data provided by the European Centre for Medium-Term Weather Forecasting are matched with the output spatial information and urban latitude and longitude.

### Transmission effect model and variable definition

To verify the green innovation transmission effect caused by the policy, we constructed its upstream and downstream transmissions based on the input–output table data in 2012. The transmission effect model is as follows:

$$Gpatent_{it} = \beta_0 + \beta_1 for_i \times Time_t + \beta_2 back_i \times Time_t + \beta_3 Control_{it} + \mu_i + \sigma_t + \varepsilon_{it} . \tag{5}$$

In the aforementioned equation, $for_i \times Time_t$ and $back_i \times Time_t$ represent the downstream and upstream transmission effects, respectively.

The calculation method for the downstream transmission of the regulated industry is as follows:

$$for_i = \sum_{f \neq i} \left( input_{if} \Big/ \sum_f input_{if} \right) \times Rg_f. \tag{6}$$

In the aforementioned equation, $i$ and $f$ denote different industries, and $i$ is the downstream industry of $f$; $input_{if}$ represent the total amount of products of industry $f$ used in industry $i$; $\Sigma_f input_{if}$ represents all intermediate inputs in industry $i$; and $Rg_f$ is the regulated status of industry $f$. If industry $f$ is a regulated industry, then $Rg_f = 1$; otherwise $Rg_f = 0$.

The calculation method for the upstream transmission of the regulatory industry is as follows:

$$back_i = \sum_{f \neq i} \left( output_{if} \Big/ \sum_f output_{if} \right) \times Rg_f. \tag{7}$$

In the aforementioned equation, $f$ is the downstream industry of $i$, $output_{if}$ indicates the total input of industry $i$ as intermediate products into industry $f$, and $\Sigma_f output_{if}$ represents the total input of all intermediate products in industry $i$.

### Price transmission mechanism model and variables

To further verify the price transmission mechanism, we build a price transmission effect model. First, we need to verify the price promotion effect of the pilot policy:

$$Pfluc_{ijt} = \beta_0 + \beta_1 Treat_{ij} \times Time_t + \beta_2 Control_{jt} + \mu_{ij} + \sigma_t + \varepsilon_{ijt}. \tag{8}$$

In the aforementioned equation, $i$ is the region and $j$ is the industry, $Treat_{ij}$ represents regulated industries in the pilot area, and $Pfluc_{ijt}$ are the fluctuations in prices. We select the ex-factory price index (previous year's price $= 100$) of industrial producers in each province and industry in the "China Price Statistics Yearbook" as an intermediary variable to explore whether the carbon emission trading policy increases the production price of regulated industries in the pilot area. On the basis of the province's two-digit industry

price index data from 2012 to 2019, we construct a difference model for regression. The influence of variables (*Pcontrol*) at the provincial level is considered, including consumer and fixed asset investment price indexes (from "China Statistical Yearbook").

Second, we construct a model to test the effect of price fluctuation on green innovation of downstream enterprises.

$$
\begin{aligned}
Gpatent_{it} = {} & \beta_0 + \beta_1 Forprice_i \times Time_t + \beta_2 Backprice_i \times Time_t \\
& + \beta_3 Control_{it} + \mu_i + \sigma_t + \varepsilon_{it}.
\end{aligned}
\tag{9}
$$

In the aforementioned equation, $Forprice_i$ and $Backprice_i$ represent the upstream and downstream price fluctuation transmission indicators, respectively.

Using the 2012 inter-regional input–output table, we refer to the construction method of the network transmission intensity, and using price fluctuation data, we construct an upstream price fluctuation index *(Forprice$_i$)*. The calculation method is as follows:

$$
Forprice_i = \sum_f \left[ \left( input_{if} \Big/ \sum_f input_{if} \right) \times Pfluc_f \right].
\tag{10}
$$

In the aforementioned equation, $i$ denotes the downstream of industry $f$, $input_{if}$ represents the total amount of products in industry $f$ used in industry $i$, $\Sigma_f input_{if}$ indicates the total amount of all intermediate inputs in industry $i$, and $Pfluc_f$ is the price fluctuations in industry $f$, which is the increase in current prices from the previous period.

Similarly, we construct a downstream price fluctuation transmission indicator (*Backprice$_i$*):

$$
Backprice_i = \sum_f \left[ \left( output_{if} \Big/ \sum_f output_{if} \right) \times Pfluc_f \right].
\tag{11}
$$

In the aforementioned equation, $f$ is the downstream industry of $i$, $output_{if}$ is the total input of industry $i$ as intermediate products into industry $f$, $\Sigma_f output_{if}$ is the total amount of all intermediate products in industry $i$, and $Pfluc_f$ represents the price fluctuations of industry $f$, which is the increase in current prices from the previous period.

Furthermore, we split price fluctuations into those in regulated industries in pilot and other regions. Four variables of upstream price fluctuations are constructed in regulated industries (*Regfor*), upstream price fluctuations in other industries (*Nregfor*), downstream price fluctuations in regulated industries (*Regback*), and downstream price fluctuations in other industries (*Nregback*) (calculation methods are similar to Eqs. 10 and 11).

## Results

### Parallel trend test

The parallel trend hypothesis is the key falsehood of the DID model and is tested in this study. We set the gap in the number of green patent applications between the experimental and control groups in 2012 as a baseline of 0 with a confidence interval of 95%. Figure 1 demonstrates that before 2014, the number of green patent applications in the experimental and control groups have no significant gap. Thus, the parallel trend hypothesis is satisfied. After the policy implementation, the number of green

**Fig. 1** Results of the parallel trend test
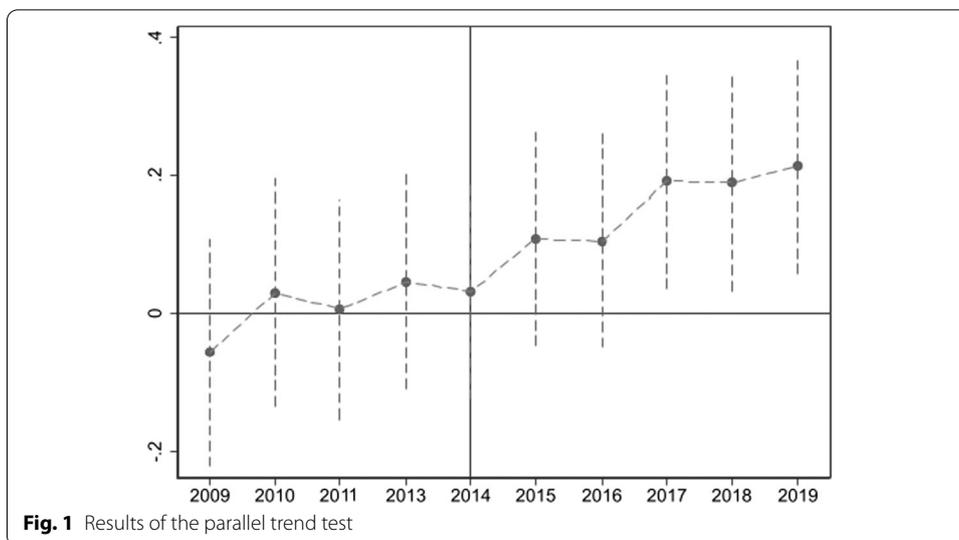
patent applications in the experimental group significantly increases compared with the control group.

## Baseline results

Table 3 reports the benchmark regression results. In Model (1), we consider the time and firm fixed effects. The coefficient of *Treat × Time* is positive and significant at the 1% level, indicating that after implementing the China's carbon emission trading policy, the number of green patent applications by regulated companies significantly increases. In Model (2), we further add control variables at the enterprise level. The empirical results reveal that the green innovation promotion effect of carbon emission trading policy remains significantly positive. The benchmark regression results verify Hypothesis 1, indicating that the market behavior of carbon emissions trading using financial leverage to promote market flow is conducive to corporate green innovation.

## Dynamic effects

To analyze the dynamic effect of the policy on green innovation, we construct a multiplication term between the regulated company and year, considering time fixed effects, corporate fixed effect, and corporate-level variables. In addition, we add policy effects in different years. Model (3) in Table 4 shows that the experimental and control groups in the first year of policy implementation have no apparent difference, but after 2014, the significance of the impact gradually increases from 10 to 1%. As for the crossover term, the estimated coefficients are 0.114, 0.115, 0.183, and 0.189 in 2015, 2016, 2017, and 2019, respectively. The results reveal a certain time lag in the impact effect that is increasing year by year. In Model (4), we consider firm and industry-time level fixed effects to analyze the impact of individual time effects, and the regression results remain significantly positive.

**Table 3** Benchmark regression results

| Variable | (1) Gpatent | (2) Gpatent |
|---|---|---|
| *Treat × Time* | 0.107*** (0.0357) | 0.136*** (0.0413) |
| *Age* |  | 0.292*** (0.0614) |
| *Scale* |  | 0.209*** (0.0100) |
| *Dar* |  | −0.015 (0.0359) |
| *Roe* |  | −0.001 (0.0008) |
| *Tat* |  | −0.030** (0.0127) |
| *Cr* |  | −0.015*** (0.0051) |
| *Qr* |  | 0.015*** (0.0051) |
| *Mfr* |  | 0.002 (0.0030) |
| Constant | 0.511*** (0.0036) | −4.894*** (0.2760) |
| Firm | Yes | Yes |
| Year | Yes | Yes |
| Observations | 25,329 | 24,533 |
| Adjust $R^2$ | 0.705 | 0.720 |

The coefficient values in parentheses are the robust standard errors of the corresponding regression coefficients

***, **, *Significance levels of 1%, 5%, and 10%, respectively

### Robustness test

#### Introducing the instrument variable

To alleviate the endogeneity of the initial conclusion, we use a two-stage instrumental variable regression. Regression results are reported in Models (5) and (6) in Table 5. Model (5) indicates a significant reverse relationship between the ventilation coefficient and choice of regulated enterprises. Model (6) shows a significantly positive effect on the green innovation of regulated enterprises. Thus, the conclusion is still stable after controlling the endogenous problems owing to the missing variables.

#### Replacing the explained variable

We replace the explanatory variable with the number of applications for a corporate green utility model patent (*Gutility*). Compared with green invention patents, green utility model patents have lower innovation requirements and reflect the level of green innovation of enterprises to a certain extent. Model (7) shows that the effect of the carbon emission trading policy on green innovation is significantly positive, which further verifies the conclusion of the benchmark regression.

**Table 4** Dynamic effects

| Variable | (3) | (4) |
|---|---|---|
|  | **Gpatent** | **Gpatent** |
| *Treat × Year2014* | 0.039 (0.0622) |  |
| *Treat × Year2015* | 0.114* (0.0620) |  |
| *Treat × Year2016* | 0.115* (0.0612) |  |
| *Treat × Year2017* | 0.182*** (0.0611) |  |
| *Treat × Year2018* | 0.182*** (0.0613) |  |
| *Treat × Year2019* | 0.189*** (0.0613) |  |
| *Treat × Time* |  | 0.138*** (0.0401) |
| Constant | − 4.907*** (0.2360) | − 4.912*** (0.2750) |
| *Control* | Yes | Yes |
| Firm | Yes | Yes |
| Year | Yes |  |
| Industry-Year |  | Yes |
| Observations | 24,533 | 24,533 |
| Adjust R$^2$ | 0.720 | 0.721 |

***, **, *Significance levels of 1%, 5%, and 10%, respectively

**Table 5** Robustness test

| Variable | (5) | (6) | (7) | (8) |
|---|---|---|---|---|
|  | **Treat × Time** | **Gpatent** | **Gutility** | **Gpatent** |
| *Treat × Time* |  | 1.515*** (0.5410) | 0.072** (0.0347) | 0.102*** (0.0365) |
| *lnVc* | − 0.037*** (0.0034) |  |  |  |
| *Control* | Yes | Yes | Yes | Yes |
| Industry | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| Observations |  | 24,522 | 24,694 | 21,686 |
| Adjust R$^2$ |  | 0.173 | 0.693 | 0.715 |
| F | 97.68 |  |  |  |

***, **, *Significance levels of 1%, 5%, and 10%, respectively

### *PSM–DID*

To reduce the statistical result bias caused by the self-selection problem of the experimental group, we use the PSM method to screen the experimental and control groups to reduce their natural gap. Based on their data in 2013, we use company-level variables as covariates and corporate green innovation as the result variable. In addition, radius matching is used to screen the experimental and control group companies, and the matched samples are used to conduct DID analysis. Figure 2 illustrates the results of the balance test for PSM. Before the match, the experimental and control groups

**Fig. 2** Balance test results
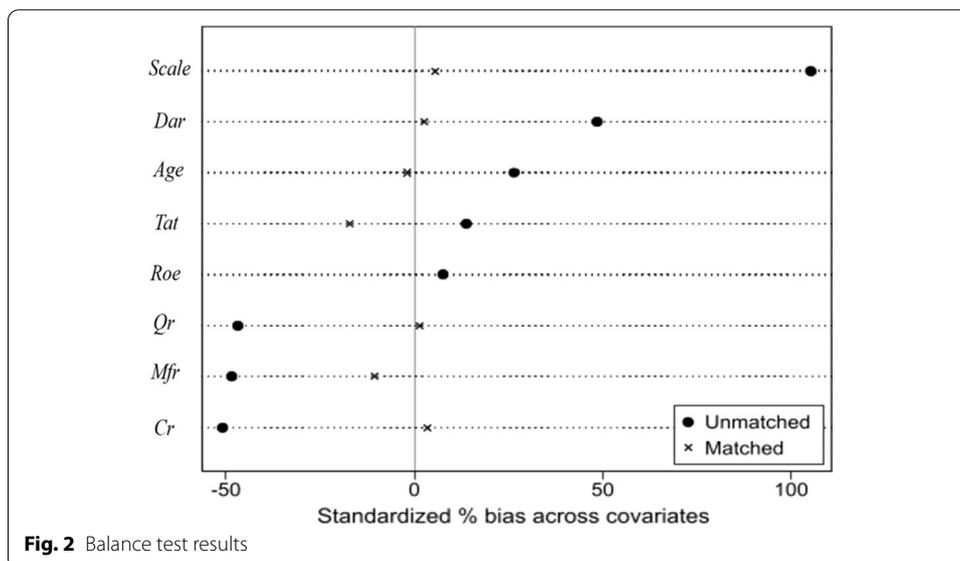
exhibited a huge gap, which significantly decreased after the match. Model (8) presents the PSM–DID robustness regression results. The *Treat × Time* coefficient decreases but is significantly positive, which further verifies the conclusion of the benchmark regression. Thus, the financial nature of carbon emissions trading is conducive to corporate green innovation.

### Heterogeneity analysis

Based on the characteristics of the geographic location and equity nature, we further analyze the heterogeneous effect of the carbon emission trading policy on corporate green innovation. Models (9) and (10) in Table 6a demonstrate the green innovation effects of the policy in different regions. The impact of the policy on green innovation is mainly reflected in the eastern region but is not as apparent in the central and western regions. The eastern region has a higher level of marketization, and enterprises can obtain more innovative resources through the market. In addition, their economic activities have become more frequent and the accumulation of green innovation resources has become more abundant. At the same time, the financial innovation atmosphere in the eastern region is relatively strong. Financial innovation and expansion of relevant services promote inclusion in carbon emissions trading. Therefore, as affected by policy shocks, the eastern region is more likely to force companies to perform green innovations.

Models (11) and (12) show the green innovation effect of the policy in companies with different equity properties. The results reveal that the policy's impact on green innovation is mainly reflected in state-owned enterprises (SOEs) and not as apparent in private firms. The possible reasons are as follows. First, 70% of regulated enterprises are SOEs, which are more heavily affected by policies compared with private firms. Moreover, the competition objective of SOEs differs from that of private firms. In addition, SOEs assume more social leading obligations and become more active at the level of green technological innovation.

Yu *et al. Financial Innovation*        (2022) 8:55

Page 16 of 24

**Table 6** Results of heterogeneity test

| Variable | (9) | (10) | (11) | (12) | (13) | (14) |
|---|---|---|---|---|---|---|
| | *Gpatent* | *Gpatent* | *Gpatent* | *Gpatent* | *Gpatent* | *Gpatent* |
| | Eastern area | Central and Western area | State-owned | Privates | High subsidy | Low subsidy |
| **(a)** | | | | | | |
| *Treat × Time* | 0.188*** (0.0499) | − 0.0742 (0.0661) | 0.120** (0.0514) | 0.0938 (0.0616) | 0.0856 (0.0584) | 0.167*** (0.0551) |
| Constant | − 5.640*** (0.4000) | − 4.286*** (0.5394) | − 6.702*** (0.5448) | − 5.030*** (0.3672) | − 5.128*** (0.4341) | − 5.135*** (0.4221) |
| *Control* | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm | Yes | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 16,745 | 7949 | 9320 | 15,374 | 11,142 | 11,548 |
| Adjust $R^2$ | 0.737 | 0.674 | 0.771 | 0.674 | 0.705 | 0.725 |

| Variable | (15) | (16) | (17) | (18) |
|---|---|---|---|---|
| | *Gpatent* | *Gpatent* | *Gpatent* | *Gpatent* |
| | High Tobin Q | Low Tobin Q | High financing constraints | Low financing constraints |
| **(b)** | | | | |
| *Treat × Time* | 0.138*** (0.0503) | 0.0938 (0.0616) | − 0.0237 (0.0881) | 0.0890* (0.0466) |
| Constant | − 6.702*** (0.5454) | − 5.030*** (0.3674) | − 5.528*** (0.3871) | − 6.088*** (0.5145) |
| *Control* | Yes | Yes | Yes | Yes |
| Firm | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| Observations | 9320 | 15,374 | 9499 | 10,694 |
| Adjust $R^2$ | 0.771 | 0.674 | 0.572 | 0.766 |

| Variable | (19) | (20) | (21) | (22) |
|---|---|---|---|---|
| | *Gpatent* | *Gpatent* | *Gpatent* | *Gpatent* |
| | State-owned High subsidy | State-owned Low subsidy | Privates High subsidy | Privates Low subsidy |
| **(c)** | | | | |
| *Treat × Time* | − 0.00257 (0.0744) | 0.192*** (0.0707) | 0.112 (0.0976) | 0.0189 (0.0827) |
| Constant | − 6.805*** (0.9647) | − 7.272*** (0.8559) | − 5.751*** (0.6175) | − 4.931*** (0.5213) |
| *Control* | Yes | Yes | Yes | Yes |
| Firm | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| Observations | 3872 | 5191 | 6589 | 5690 |
| Adjust $R^2$ | 0.779 | 0.784 | 0.658 | 0.641 |

***, **, *Significance levels of 1%, 5%, and 10%, respectively

Next, we divide all companies into high and low groups based on their Tobin Q, financing constraints, and proportion of government subsidies to verify the green innovation effect of the policy in different groups of companies. The grouping is based on the size of the three company variables in 2013. The value of the previous period before

the policy implementation is used as the calculation standard, and companies with values greater than the median constitute the high group. Models (13) and (14) show the green innovation effect of the policy in high- and low-subsidy enterprises. The effect is only effective for low-subsidized companies. The possible reason is that high-subsidized companies are too powerful to receive government support and are more likely to have path dependence on government subsidies. At the same time, the difference in subsidies amplifies the uncertainty of the carbon emission market. Companies with high subsidies are not highly dependent on financial innovation generated by carbon emissions trading and thus are not active enough in green innovation. However, intuitively, SOEs may have more government subsidies than private firms, and therefore, the aforementioned conclusions may be contradictory. To further verify these results, we divide all the samples into four parts according to equity and subsidy intensity and then conduct empirical analysis. Table 6c reports the results. As presented by Models (19)–(22), the key explanatory variables are significantly positive only in the low subsidy intensity SOEs group, which indicates they have significant green innovation effect.

Models (15) and (16) in Table 6b show that the policy has a green innovation effect in enterprises with high Tobin Q, which refers to the ratio of the market value of capital to its replacement cost. These enterprises have higher market values, which indicates better future prospects (Ding et al. 2020) and more sources of green innovation resources from the market. Models (17) and (18) show that the policy has a green innovation effect on companies with low financing constraints, which pose a challenge of external financing for companies (Ullah et al. 2021). Companies with low financing constraints can obtain more green innovation resources from the market, which is consistent with reality. This result shows that improving the carbon financial derivatives trading mechanism, expanding the channels for obtaining carbon financial products and services, increasing the scale of transactions, and reducing the financing constraints of enterprises may better stimulate corporate innovation.

## Network conduction effect

### Analysis of conduction trend

Based on the upstream and downstream transmission intensity variables, we conduct a parallel trend test. The premise for the effective transmission conclusion is that before the upstream and downstream shocks, the upstream and downstream affiliated and non-affiliated companies have no significant differences in green innovation. We use 2012 as a benchmark to draw parallel trend test charts for upstream and downstream shocks, with the confidence interval set at 95% and the dotted line as the year when the policy occurs. Figure 3 illustrates the downstream conduction effect. Before 2014, green patent applications in high- and low-relevance industries show no significant gap. This result basically verifies the hypothesis of parallel trends. After implementing the policy, green patent applications in high-relevance industries significantly increase compared with that of low-relevance industries. Figure 4 shows the upstream conduction effect. Before 2014, green patent applications in high- and low-relevance industries show no significant gap. After implementing the policy, green patent applications in high-relevance industries significantly decrease compared with that of low-relevance industries.

**Fig. 3** Downstream conduction effect and parallel trend test



**Fig. 4** Upstream conduction effect and parallel trend test
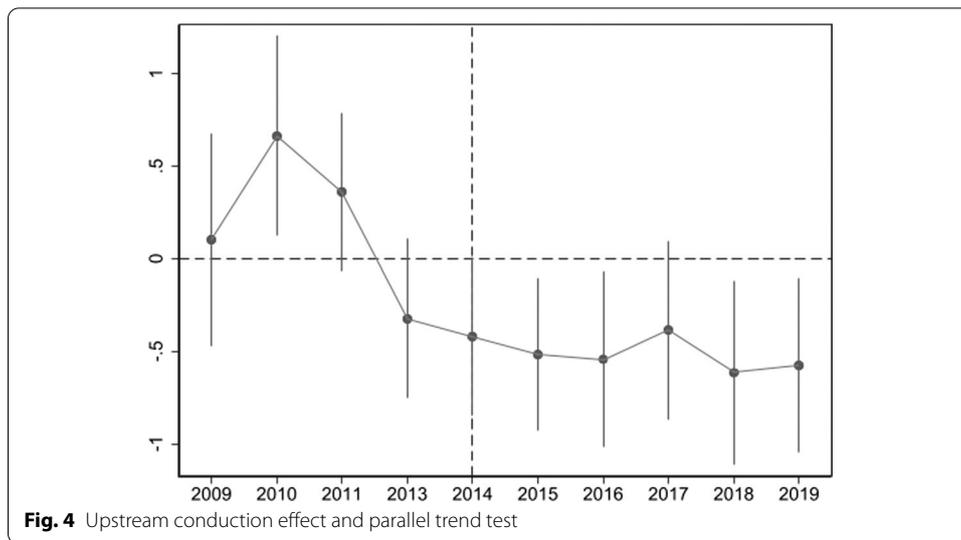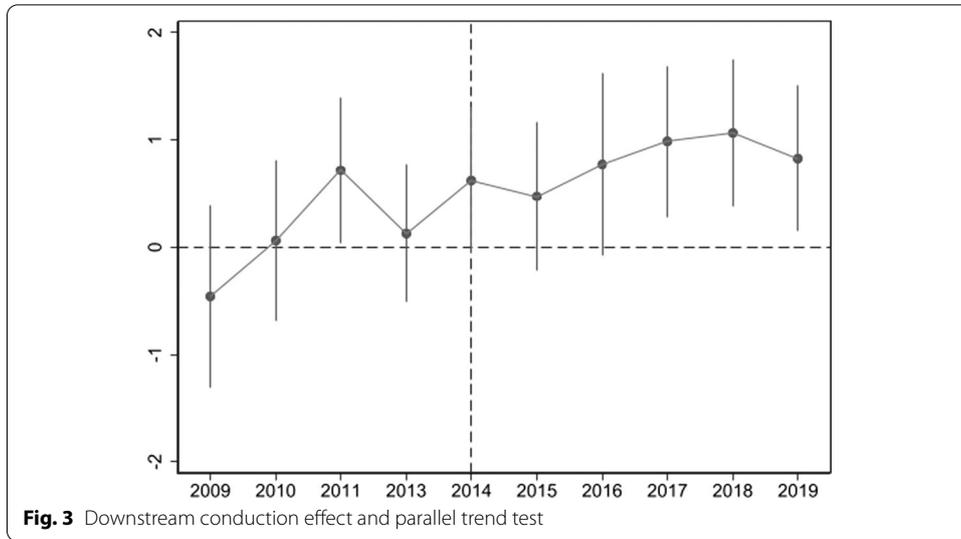
Table 7 reports the empirical results of the conduction effect, where *Back × Time* and *For × Time* represent the upstream and downstream conduction effects, respectively. After adding firm-level characteristic variables, the firm and time fixed effects, both Models (23) and (24) show that the coefficient of *Back × Time* is significantly negative, whereas that of *For × Time* is positive. The results show that the carbon emission rights trading policy has a significant downstream green innovation transmission effect but inhibits the green innovation of the upstream industry, thereby verifying Hypotheses 2 and 3, respectively. For relatively upstream companies, the policy-induced cost increases, and capacity conversion in the regulated industry reduces the demand for upstream products and ultimately increases their green

Yu *et al. Financial Innovation*    (2022) 8:55

Page 19 of 24

**Table 7** Conduction effect test

| Variable | (23) Gpatent | (24) Gpatent | (25) Gpatent |
|---|---|---|---|
| *Back × Time* | − 0.625*** (0.1404) | − 0.578*** (0.1410) | |
| *For × Time* | 0.808*** (0.2060) | 0.675*** (0.2110) | |
| *Back × Year2014* | | | − 0.364* (0.2187) |
| *Back × Year2015* | | | − 0.414** (0.1978) |
| *Back × Year2016* | | | − 0.607** (0.2687) |
| *Back × Year2017* | | | − 0.532** (0.2490) |
| *Back × Year2018* | | | − 0.893*** (0.2675) |
| *Back × Year2019* | | | − 0.689*** (0.2359) |
| *For × Year2014* | | | 0.384 (0.3328) |
| *For × Year2015* | | | 0.270 (0.3324) |
| *For × Year2016* | | | 0.680 (0.4489) |
| *For × Year2017* | | | 0.853** (0.3411) |
| *For × Year2018* | | | 1.125*** (0.3330) |
| *For × Year2019* | | | 0.783** (0.3251) |
| Constant | 0.469*** (0.0053) | − 5.004*** (0.3326) | − 5.149*** (0.3592) |
| *Control* | | Yes | Yes |
| Firm | Yes | Yes | Yes |
| Year | Yes | Yes | Yes |
| Observations | 19,029 | 18,914 | 20,841 |
| Adjust R$^2$ | 0.621 | 0.683 | 0.703 |

***, **, *Significance levels of 1%, 5%, and 10%, respectively

innovation costs. For relatively downstream companies, the increase in product prices in the regulated industry forces them to improve utilization efficiency, actively explore alternatives, and increase the willingness to perform green innovation. Model (25) reports the dynamic effects of the upstream and downstream conduction. In the current period of policy implementation, green innovation in upstream industries significantly decreases. The upstream industry is relatively quickly affected by policy transmission, and the inhibitory effect on their green innovation gradually increases. At the same time, in the first three phases of policy implementation, downstream industries are less affected by policy shocks and transmission, but the green innovation promotion effect of policies on downstream industries gradually increases.

**Table 8** Transmission mechanism test results

| Variable | (26) Pfluc | (27) Pfluc | (28) Gpatent | (29) Gpatent |
|---|---|---|---|---|
| Treat × Time | 2.8365*** (0.4043) | 2.9494*** (0.4036) | | |
| Forprice | | | 0.534* (0.2880) | |
| Backprice | | | 0.0445 (0.0526) | |
| Regfor × Time | | | | 0.644*** (0.1864) |
| Nregfor × Time | | | | 0.276*** (0.0640) |
| Regback × Time | | | | −0.229 (0.1520) |
| Nregback × Time | | | | −0.0160 (0.0485) |
| Constant | 99.76*** (0.0901) | 53.27** (22.3112) | −5.198*** (0.5451) | −5.025*** (0.5304) |
| Pcontrol | | Yes | | |
| Control | | | Yes | Yes |
| Province-Industry | Yes | Yes | | |
| Firm | | | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| Observations | 8938 | 8778 | 16,284 | 16,284 |
| Adjust $R^2$ | 0.266 | 0.267 | 0.770 | 0.770 |

***, **, *Significance levels of 1%, 5%, and 10%, respectively

### Conduction mechanism inspection

#### Direct evidence: policy shock and price index

Models (26) and (27) present the empirical results of the pilot policy on price volatility and indicate the significantly positive effect of carbon trading policy on the ex-factory prices of the regulated industries in the pilot region (*Pfluc*).

#### Transmission mechanism: price fluctuation

Model (28) in Table 8 shows the impact of upstream and downstream price fluctuations on the industry's green innovation. The results show that the upstream industry's lagging price increase significantly enhances the industry innovation level, but the downstream price increase has no significant impact.

The four variables are cross-multiplied with the time of policy occurrence and included in Model (29). The results show that price fluctuations in other industries that are not directly affected by the policies have a significantly positive impact on the green innovation of downstream industries but no significant impact on upstream innovation. The price volatility of the regulated industry shows the same trend. However, the impact on downstream industries has a relatively large coefficient. This cost-reversal mechanism further promotes the green innovation of downstream enterprises. The lack of innovation motivation of upstream companies is due to the low degree of carbon finance innovation in China. The price mechanism of carbon

Yu *et al. Financial Innovation*      (2022) 8:55

Page 21 of 24

emissions trading affecting innovation is more subject to nonmarket shocks, and the cost reduction effect owing to carbon emissions exchanges is not prominent for upstream companies.

## Conclusions and suggestions

This study constructs a more credible sample by matching the directory of companies trading in the Chinese carbon market to verify the green innovation effect of carbon emissions trading policies. While extant literature mainly addresses the impact of policies on regulated industries, the current study emphasizes the innovation spillovers triggered by policies based on the production network transmission, with the following findings.

First, the policy significantly enhances the green innovation level of regulated firms on average, and dynamically, this effect increases with each passing year in both statistical and economic significance. In further robustness tests, we alleviate the possible endogeneity problem through instrumental variables and PSM, thereby ensuring the credibility of conclusions and the validity of the Porter hypothesis.

Second, the innovation effect of the policy has a clear heterogeneous feature. At the macro level, compared with the central and western regions, the eastern region has a high degree of marketization and is more conducive to firm innovation. At the micro level, companies that are less affected by government subsidies and have strong financing capacity have higher levels of green innovation than other firms.

Finally, the innovation spillover effect of the policy suggests upstream and downstream asymmetry. On the one hand, the increase in R&D costs of regulated firms eventually depletes the product demand for upstream firms, thereby reducing their willingness to innovate. On the other hand, green innovation by regulated firms provides cleaner finished products for downstream firms. The higher prices for finished products force these firms to improve utilization efficiency, thereby promoting their innovation.

The aforementioned findings are important guidance for a comprehensive assessment of policy effects, for which three suggestions are provided.

First, various derivatives must be introduced to mobilize the market and reduce the speculative volatility of carbon prices. The carbon sequestration market has apparent policy characteristics. While giving full play to the market mechanism, ensuring the relative stability of prices is necessary. In the early stage of market construction, the system is not perfect, and certain administrative measures can be used to combat speculation and correct system loopholes. Taking advantage of the functions of carbon emission rights in the resource allocation to gradually reduce the impact of nonmarket factors on prices.

Second, it is imperative to develop relevant supporting policies to encourage enterprise innovation and reduce the crowding-out effect caused by emissions reduction. The implementation of policy needs to balance fairness and efficiency. While regulating the internalization of pollution costs, enterprises also face more severe pressures for cleaner production and have stronger motivations for innovation. With reference to the supporting carbon sink policies of the European Union and other countries, an innovation fund is established to encourage relevant companies to ease their cost constraints.

Lastly, nonmarket factors that impede network transmission must be eliminated, and market frictions must be reduced. The effect of policy implementation between the east and west has a huge difference. One possible reason is that the central and western regions have more administrative factors that hinder the transmission. These factors reduce institutional transaction costs, reasonably reduce energy costs, promote interprovincial trade, and unblock the production network transmission mechanism to prevent unnecessary losses. Considering the spillover effect of policies, the innovation effect of upstream enterprises in regulated industries needs more attention. This negative impact can be alleviated using financial assistance and external resources.

Furthermore, this study presents few limitations. First, owing to the sample limitation, we only consider the regulated companies, considering the systematic differences in innovation capabilities between listed and nonlisted companies, and heterogeneous impact of policies on innovation needs to be further verified by data. Second, we use the interregional input–output table in 2012 to measure the upstream and downstream linkages among firms. However, existing studies suggest that production networks may be endogenous and the input–output among firms may fluctuate owing to factors such as prices. Therefore, future directions can consider two directions for improvement. First, survey data can be used to precisely identify the heterogeneous effects of policies on different types of firms. Second, information on firms' supply chains can be obtained and whether policies change their input–output associations can be determined.

## Declarations

**Competing interests**
All Authors declare that they have no competing interest.

**Author details**
[1]Faculty of Business Economics, Shanghai Business School, Shanghai 200235, China. [2]College of Business, Shanghai University of Finance and Economics, Shanghai 200433, China. [3]College of Metropolitan Transportation, Beijing University of Technology, Beijing 100124, China. [4]Department of Management, Birkbeck, University of London, London WC1E 7HX, UK. [5]School of Accounting, Nanjing Audit University, Nanjing 211815, China. [6]School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100008, China. [7]Centre for Transport Studies, Imperial College London, London SW7 2AZ, UK.

## References

Acemoglu D, Aghion P, Bursztyn L, Hemous D (2012a) The environment and directed technical change. Am Econ Rev 102:131–166. https://doi.org/10.1257/aer.102.1.131

Acemoglu D, Carvalho VM, Ozdaglar A, Tahbaz-Salehi A (2012b) The network origins of aggregate fluctuations. Econometrica 80:1977–2016. https://doi.org/10.3982/ECTA9623

Acemoglu D, Akcigit U, Kerr W (2016) Networks and the macroeconomy: an empirical exploration. NBER Macroecon Annu 30(1):273–335. https://doi.org/10.2139/ssrn.2632793

Angrist JD, Pischke JS (2010) The credibility revolution in empirical economics: how better research design is taking the con out of econometrics. J Econ Perspect 24:3–30. https://doi.org/10.1257/jep.24.2.3

Baqaee DR, Farhi E (2019) The macroeconomic impact of microeconomic shocks: beyond Hulten's theorem. Econometrica 87:1155–1203. https://doi.org/10.3982/ECTA15202

Becker SO, Mergele L, Woessmann L (2020) The separation and reunification of Germany: rethinking a natural experiment interpretation of the enduring effects of communism. J Econ Perspect 34(2):143–171. https://doi.org/10.1257/jep.34.2.143

Bi H, Shang W-L, Chen Y, Wang K, Yu Q, Sui Y (2021) GIS aided sustainable urban road management with a unifying queueing and neural network model. Appl Energy 291:116818. https://doi.org/10.1016/j.apenergy.2021.116818

Bi H, Shang W, Wang K, Chen Y (2022) Joint optimisation for pedestrian, information and energy flows in emergency response systems with energy harvesting and energy sharing. IEEE Trans Intell Transp Syst. https://doi.org/10.1109/TITS.2022.3159503 (**in press**)

Bondy M, Roth S, Sager L (2020) Crime is in the air: the contemporary relationship between air pollution and crime. J Assoc Environ Resour Econ 7:555–585. https://doi.org/10.1086/707127

Cai B, Guo H, Ma Z, Wang Z, Dhakal S, Cao L (2019) Benchmarking carbon emissions efficiency in Chinese cities: a comparative study based on high-resolution gridded data. Appl Energy 242:994–1009. https://doi.org/10.1016/j.apenergy.2019.03.146

Carvalho VM, Tahbaz-Salehi A (2019) Production networks: a primer. Ann Rev Econ 11:635–663. https://doi.org/10.1146/annurev-economics-080218-030212

Carvalho VM, Nirei M, Saito YU, Tahbaz-Salehi A (2020) Supply chain disruptions: evidence from the great east Japan earthquake. Q J Econ 136(2):1255–1321. https://doi.org/10.1093/qje/qjaa044

Chen Z, Zhang X, Chen F (2021a) Do carbon emission trading schemes stimulate green innovation in enterprises? Evidence from china. Technol Forecast Soc Change 168(2):120744. https://doi.org/10.1016/j.techfore.2021.120744

Chen D, Gao H, Ma Y (2021b) Human capital-driven acquisition: evidence from the inevitable disclosure doctrine. Manag Sci 67(8):4643–4664. https://doi.org/10.1287/mnsc.2020.3707

De Haas R, Popov AA (2018) Financial development and industrial pollution. SSRN Electron J. https://doi.org/10.2139/ssrn.3214528

Demirgüç-Kunt A, Horváth BL, Huizinga H (2020) Foreign banks and international transmission of monetary policy: evidence from the syndicated loan market. Eur Econ Rev 129:103542. https://doi.org/10.1016/j.euroecorev.2020.103542

Ding N, Bhat K, Jebran K (2020) Debt choice, growth opportunities and corporate investment: evidence from China. Financ Innov. https://doi.org/10.1186/s40854-020-00194-1

Du G, Yu M, Sun C, Han Z (2021) Green innovation effect of emission trading policy on pilot areas and neighboring areas: an analysis based on the spatial econometric model. Energy Policy. https://doi.org/10.1016/j.enpol.2021.112431

Elahi E, Khalid Z, Tauni MZ, Zhang H, Lirong X (2021) Extreme weather events risk to crop-production and the adaptation of innovative management strategies to mitigate the risk: a retrospective survey of rural Punjab, Pakistan. Technovation. https://doi.org/10.1016/j.technovation.2021.102255

Elahi E, Khalid Z, Zhang Z (2022a) Understanding farmers' intention and willingness to install renewable energy technology: a solution to reduce the environmental emissions of agriculture. Appl Energy. https://doi.org/10.1016/j.apenergy.2021.118459

Elahi E, Zhang Z, Khalid Z, Xu H (2022b) Application of an artificial neural network to optimise energy inputs: an energy- and cost-saving strategy for commercial poultry farms. Energy 244:123169. https://doi.org/10.1016/j.energy.2022.123169

Feng D, Dai Y, Zhang S, Zhang X, Long R (2019) Can a carbon emission trading scheme generate the porter effect? Evidence from pilot areas in China. Sci Total Environ 653:565–577. https://doi.org/10.1016/j.scitotenv.2018.10.395

Gao H, Shi D, Zhao B (2021) Does good luck make people overconfident? Evidence from a natural experiment in the stock market. J Corp Financ 68:101933. https://doi.org/10.1016/j.jcorpfin.2021.101933

Greenstone M (2002) The impacts of environmental regulations on industrial activity: evidence from the 1970 and 1977 clean air act amendments and the census of manufactures. J Polit Econ 110(6):1175–1219. https://doi.org/10.3386/w8484

He J, Tian X (2018) Finance and corporate innovation: a survey. Asia-Pac J Financ Stud 47:165–212. https://doi.org/10.2139/ssrn.3062863

Hu J, Pan X, Huang Q (2020a) Quantity or quality? The impacts of environmental regulation on firms' innovation–Quasi-natural experiment based on China's carbon emissions trading pilot. Technol Forecast Soc Change 158:120122. https://doi.org/10.1016/j.techfore.2020.120122

Hu Y, Ren S, Wang Y, Chen X (2020b) Can carbon emission trading scheme achieve energy conservation and emission reduction? Evidence from the industrial sector in China. Energy Econ. https://doi.org/10.1016/j.eneco.2019.104590

Huang Q, Zheng H, Li J, Meng J, Liu Y, Wang Z, Zhang N, Li Y, Guan D (2021) Heterogeneity of consumption-based carbon emissions and driving forces in Indian states. Adv Appl Energy 4:100039. https://doi.org/10.1016/j.adapen.2021.100039

Jiang X, Xu Y, Xiao N (2012) The study of financial management information for business process reengineering under the low-carbon economy. Soft Comput Inf Commun Technol 158:5–10. https://doi.org/10.1007/978-3-642-29148-7_2

Li J, Wang F, He Y (2020) Electric vehicle routing problem with battery swapping considering energy consumption and carbon emissions. Sustainability 12(24):10537. https://doi.org/10.3390/su122410537

Li Z, Wang J, Che S (2021) Synergistic effect of carbon trading scheme on carbon dioxide and atmospheric pollutants. Sustainability 13(10):5403. https://doi.org/10.3390/su13105403

Liu E (2019) Industrial policies in production networks. Q J Econ 134(4):1883–1948. https://doi.org/10.1093/qje/qjz024

Liu K, Lin B (2018) Research on influencing factors of environmental pollution in China: a spatial econometric analysis. J Clean Prod 206:356–364. https://doi.org/10.1016/j.jclepro.2018.09.194

Liu Z, Sun H (2021) Assessing the impact of emissions trading scheme on low-carbon technological innovation: evidence from China. Environ Impact Assess Rev 89:106589. https://doi.org/10.1016/j.eiar.2021.106589

Liu Y, Tan XJ, Yu Y, Qi SZ (2017) Assessment of impacts of Hubei Pilot emission trading schemes in China—A CGE-analysis using TermCO2 model. Appl Energy 189:762–769. https://doi.org/10.1016/j.apenergy.2016.05.085

Liu Z, Lang L, Li L, Zhao Y, Shi L (2021) Evolutionary game analysis on the recycling strategy of household medical device enterprises under government dynamic rewards and punishments. Math Biosci Eng 18(5):6434–6451. https://doi.org/10.3934/mbe.2021320

Liu Z, Qian Q, Hu B, Shang W, Li L, Zhao Y, Zhao Z, Han C (2022) Government regulation to promote coordinated emission reduction among enterprises in the green supply chain based on evolutionary game analysis. Resour Conserv Recycling. https://doi.org/10.1016/j.resconrec.2022.106290

Montero JP (1998) Marketable pollution permits with uncertainty and transaction costs. Resour Energy Econ 20:27–50. https://doi.org/10.1016/S0928-7655(97)00010-9

Panizza U (2012) Finance and economic development. Int Dev Policy Aid Emerg Econ Glob Policies 3:141–160. https://doi.org/10.1007/978-1-137-00357-7_10

Rostas L, Leontief WW (1952) The structure of American economy, 1919–1939: an empirical application of equilibrium analysis. Econ J 62:908–910. https://doi.org/10.2307/2226547

Shang WL, Chen Y, Li X, Ochieng WY (2020) Resilience analysis of urban road networks based on adaptive signal controls: day-to-day traffic dynamics with deep reinforcement learning. Complexity. https://doi.org/10.1155/2020/8841317

Shang WL, Chen J, Bi H, Sui Y, Chen Y, Yu H (2021) Impacts of COVID-19 pandemic on user behaviors and environmental benefits of bike sharing: a big-data analysis. Appl Energy. https://doi.org/10.1016/j.apenergy.2020.116429

Shang W, Gao Z, Nicolo D, Long Y, Zhang H, Guo Z, Ochieng W (2022) Benchmark analysis for robustness of multi-scale urban road networks under global disruptions. IEEE Trans Intell Transp Syst. https://doi.org/10.1109/TITS.2022.3149969

Tang K, Zhou Y, Liang X, Zhou D (2021) The effectiveness and heterogeneity of carbon emissions trading scheme in china. Environ Sci Pollut Res 28:17306–17318. https://doi.org/10.1007/s11356-020-12182-0

Ullah F, Degong M, Anwar M, Hussain S, Ullah R (2021) Supportive tactics for innovative and sustainability performance in emerging SMEs. Financ Innov. https://doi.org/10.1186/s40854-021-00284-8

Wang S, Zhen L, Psaraftis NH (2021) Three potential benefits of the EU and IMO's landmark efforts to monitor carbon dioxide emissions from shipping. Front Eng Manag 8(2):310–311. https://doi.org/10.1007/s42524-020-0096-2

Wu B, Liang H, Chan S (2022a) Political connections, industry entry choice and performance volatility: evidence from China. Emerg Mark Financ Trade 58(1):290–299. https://doi.org/10.1080/1540496X.2021.1904878

Wu B, Wang Q, Fang CH, Tsai FS, Xia Y (2022b) Capital flight for family? Exploring the moderating effects of social connections on capital outflow of family business. J Int Financ Mark Inst Money 77:101491. https://doi.org/10.1016/j.intfin.2021.101491

Yang Z, Shang W, Zhang H, Garg H, Han C (2022) Assessing the green distribution transformer manufacturing process using a cloud-based fuzzy multi-criteria framework. Appl Energy. https://doi.org/10.1016/j.apenergy.2022.118687

Yu B (2022) The impact of the internet on industrial green productivity: evidence from China. Technol Forecast Soc Change 177:121527. https://doi.org/10.1016/j.techfore.2022.121527

Yu DJ, Li J (2021) Evaluating the employment effect of china's carbon emission trading policy: based on the perspective of spatial spillover. J Clean Prod 292(490):126052. https://doi.org/10.1016/j.jclepro.2021.126052

Yu H, Zhao Y, Liu Z, Liu W, Zhang S, Wang F, Shi L (2021) Research on the financing income of supply chains based on an E-commerce platform. Technol Forecast Soc Change 169:120820. https://doi.org/10.1016/j.techfore.2021.120820

Zhang HL, An WJ (2014) On innovation research of carbon finance under intermediate business in Chinese Commercial Banks. Appl Mech Mater 543–547:4417–4423. https://doi.org/10.4028/www.scientific.net/amm.543-547.4417

Zhang X, Zhang X, Chen X (2017) Valuing air quality using happiness data: the case of China. Ecol Econ 137:29–36. https://doi.org/10.1016/j.ecolecon.2017.02.020

Zhang L, Cao C, Tang F, He J, Li D (2019) Does China's emissions trading system foster corporate green innovation? Evidence from regulating listed companies. Technol Anal Strateg Manag 31:199–212. https://doi.org/10.1080/09537325.2018.1493189

Zhang Y, Li S, Luo T, Gao J (2020) The effect of emission trading policy on carbon emission reduction: evidence from an integrated study of pilot regions in China. J Clean Prod 265:121843. https://doi.org/10.1016/j.jclepro.2020.121843

Zhao X, Peng B, Elahi E, Zheng C, Wan A (2020) Optimization of Chinese coal-fired power plants for cleaner production using Bayesian network. J Clean Prod. https://doi.org/10.1016/j.jclepro.2020.122837

Zheng Y, Han W, Yang R (2021) Does government behaviour or enterprise investment improve regional innovation performance? Evidence from China. Int J Technol Manag 85(2–4):274–296. https://doi.org/10.1504/IJTM.2021.115266

## Publisher's Note