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National mitigation policy and the competitiveness of Chinese firms

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ABSTRACT

This paper analyzes the impacts of carbon intensity control introduced by China's National Plan on firm competitiveness. By exploiting plausibly exogenous variation in the mandates on carbon intensity reduction across locations, we find that the exposure to mandate significantly decreases firm's energy intensity, but does not affect firm competitiveness measured by productivity. We show that exposure to carbon intensity control causes firms to increase their low-carbon patents by 0.9% and low-carbon patent ratio by 0.2%, with no crowding-out effect on non-low-carbon innovation. Low-carbon innovation induced by the mandate increases firm outputs by expanding the size of labour inputs and fixed assets. Therefore, although exposure to mandate reduces capital productivity, the induced innovation mitigates the negative impact through input augmentation rather than improving the energy productivity or productivity on labour or capital. This explains why mandated intensity-based policy can be an effective instrument for mitigating the greenhouse gases without harming firm competitiveness.

1. Introduction

When the command-and-control is efficient over market mechanism is a question with no simple answers (Stavins, 1995). Empirical evidences have shown that the prevailing view on the inefficiency of command-and-control over economic instruments is inaccurate (Goulder and Parry, 2008; Gray and Shimshack, 2011). Command-and-control is likely to be at least as efficient as taxes when the abatement costs are relatively low and the monitoring costs are relatively high (Cole and Grossman, 1999). Thus, the efficacy of command-and-control over effluent taxes or emission trading depends on institutional and technological conditions. In this paper, we address this question by investigating the efficiency of a regulatory based policy instrument on firm competitiveness in the context of China.

Examining the efficiency of regulatory approach in China is important and relevant for at least three well justified reasons. First, China's institutional setting implies most of its policies are command driven, despite it has attempted to lower the governmental intervention through marketization. The unique policy making structure provides an interesting example to be compared with economies where the institution is driven by democratic system. Second, China's industry productivity remains lower than the world average (Inklaar and Diewert, 2016), the experience from China is applicable to countries with similar level of industrial development for environmental control. Third, as the country with the highest level of emissions, the success of environmental related policy has strong implications for the mitigation of global climate change.

Our main objective in this paper is to estimate the effects of carbon reduction mandates on firm's competitiveness. To achieve the carbon mitigation committed in the 2009 Copenhagen Accord, China launched a greenhouse gases control policy, which was to reduce carbon intensity by 17% from the level of 2010 by 2015 during 12th Five-Year-Plan. The national target was allocated to provinces by the Chinese State Council according to some regional factors such as economic development, historical carbon emissions and potential reduction ability. Moreover, key industries like power and heating, chemical, iron and steel industries that are the major contributors of carbon emissions were required to establish corresponding emissions standards. By decentralizing the carbon intensity reduction to local governments, the greenhouse gases control policy was effective, and the carbon reduction goals were fulfilled at the end of 12th Five-Year-Plan, with carbon intensity reduced by about 20%. However, there is little known about the effects

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of such reduction mandates on firms. Does this mandated target-based regulation damage the firm's performance or spur the firm's innovation as explained by Porter and der Linde (1995)? Do firms respond to carbon intensity control in the ways similar to carbon tax or emissions trading?

We seek to identify whether carbon reduction mandates stimulate firm's low-carbon innovation and crowd out innovation in other areas, and whether such reduction mandates influence firm's competitiveness measured by firm's total factor productivity (TFP). To do so, we construct a unique and novel Chinese firm-level dataset covering the 2003–2015 period. We obtain the information on the listed companies and its subsidiaries and match detailed information on firm-level patents. As firms are generally exposed to serious shock in carbon-intensive industries in provinces with higher reduction target, we measure the variations in the policy shock from three aspects: the time variation, by distinguishing before and after the start of the 12th Five-Year Plan; the provincial variation, by comparing provinces with high mandated target versus provinces with low mandated target; and the industrial variation, by taking into account the intensity discrepancy across industries. Given that one listed company in China has multiple subsidiaries in different locations (provinces) and in different industries, the firm's exposure to carbon emissions control is measured as the average of all its subsidiaries' exposures to capture the true effects of the mandates, by employing a modified difference-in-difference-in-differences (DDD) approach. We further rule out concurrent policy shocks including Clean Production Audit, Key Pollution Monitoring Programs, and regional pilot emission trading schemes, which pose threats to the validity of our causal inference. In addition, we conduct a series of robustness checks to verify the consistent causal effects.

We have obtained novel and important findings. First, the main results show that although carbon reduction mandates spur the low-carbon innovation, the policy has no significant crowding-out effect on the innovation in other areas, and no significant negative effect on firm's TFP. In addition, the effect on low-carbon innovation exhibits heterogeneity in different dimensions. For state-owned firms, it stimulates the ratio of low carbon patent; For non-state-owned firms, it stimulates the number of low carbon patent. In terms of patent type, significant positive effect is found on low carbon utility model while the effect on invention patent is not significant. Lastly, we try to explore the potential channels through which the mandates affect firm's competitiveness. We find that exposure to mandate directly decreases the firm's capital productivity as resources are used to reduce energy intensity for meeting the mandate requirements. However, the low-carbon innovation induced by such mandate has significant positive effect on firm's output. The increase in output is the results of expansion in the size of labour inputs and fixed assets associated with innovation. The induced innovation does not improve energy productivity associated with either labor or capital inputs. Therefore, we conclude that although exposure to mandate reduces capital productivity, the induced innovation mitigates the negative impact through scale effects rather than improving the energy productivity associated with labour and capital. This explains why mandated intensity-based policy can be an effective instrument for mitigating the greenhouse gases without harming firm competitiveness.

We believe this paper makes several key contributions to the literature and to the policy discussion. First, it complements to the ongoing discussions on policy instruments for carbon mitigation. Market-based instruments have been long argued to be more efficient in reducing negative environmental externalities relative to the command and control approach (Carlson et al., 2000). Consequently, most prior studies focus on the impacts of market-based environmental regulation on firms when it comes to carbon emissions (Martin et al., 2014a, 2014b; Martin et al., 2016; Cui et al., 2018; Teixidó et al., 2019). There are also some theoretical comparisons between compare command and control policy and market-based instruments such as Dissou (2005), Fischer and Springborn (2011), Holland (2012) and Böhringer et al. (2017). The impacts of command and control policy have been widely studied in the context of pollution. These studies focus on the effects of regulation on industrial activity (Becker and Henderson, 2000; Greenstone, 2002), firm or plant-level productivity (Berman and Bui, 2001; Gray and Shadbegian, 2003; He et al., 2020) and firm's location choice (Lin and Sun, 2016; Wu et al., 2017). However, few empirical studies are found in literature when it comes to carbon emissions.[1] This study provides systematic evidence on the effects of mandated target-based regulation scheme on firm's competitiveness from China. Our paper therefore adds to literature on the understanding the environmental and economic impacts of carbon emissions control policies.

Second, this study unpacks the underlying mechanisms on how firms respond to carbon control mandates. One of the eminent hypotheses in the field of environmental regulation is Porter's induced innovation, examples include Jaffe and Palmer (1997), Berman and Bui (2001), Lanoie et al. (2008), Yang et al. (2012), Ambec et al. (2013), Rexhäuser and Rammer (2014), Cohen and Tubb (2018), Qiu et al. (2018), Stoever and Weche (2018), Peng et al. (2021). Cohen and Tubb (2018) conclude that it is more likely to find a positive effect of environmental regulation at the state, region or country level, compared to facility, firm or industry level – although in both cases the most likely scenario is statistical insignificance. In our context, we find the mandates on carbon intensity reduction do stimulate the low-carbon innovation and have no significant crowding-out effect on the innovation in other areas and insignificant negative effect on the firm's TFP. In addition, we also find the mandates significantly decrease the firm's energy intensity and increase the fixed assets. The induced low-carbon innovation significantly increases the firm's output through input augmentation.

Our third key contribution is to the policy discussion on the intensity-based approach. Both absolute and intensity-based mitigation have been discussed and implemented in countries including the US and China (Gollop and Roberts, 1983; Lin and Sun, 2016; Wu et al., 2017). Empirical studies have evidenced that both approaches are effective in curbing environmental emissions. This paper also highlights an unintended weakness of intensity-based approach in addition to the firm competitiveness. We show that the intensity-based regulation induces low-carbon innovation, mainly spurring relatively low-quality innovation measured by utility patents. As the intensity-based mandate does not affect firm competitiveness, it can serve as a good supplement to the market-based policy instrument which is widely adopted in carbon mitigation due to its cost-effectiveness. However, we shall pay special attention to the unintended consequence that it may have on firm innovation.

Finally, this study also speaks to the literature discussing the binding carbon emission reduction targets in China. Some papers study China's 2020 carbon intensity reduction target. For example, Wang et al. (2011) discuss the provincial low-carbon energy policy in the path toward achieving China's 2020 carbon reduction target. Yuan et al. (2012) examine the 2020 carbon intensity target and its interdependence with the overarching national economic development goals. Wang and Liang (2013) further investigate the integrated impacts of consumption structure changes, energy technology development, and new energy increments on China's CO2 mitigation target as well as identifying key economic sectors for achieving this target. Cui et al. (2014) explore how the emission trading scheme save cost for achieving China's 2020 carbon intensity reduction target. Other recent studies discuss the carbon neutrality target. These studies include Abbasi et al. (2021) for the UK, Shao et al. (2021) for the US, Zhang et al. (2021) for China. However, these previous studies mostly focus on macro-level analysis, the micro-level analysis on the emissions reduction target is rare. This study highlights the effect of such a binding carbon emission reduction target on the firm's performance. We find convincing evidence that intensity-based reduction target stimulates firm's low-carbon innovation but has

[1] Several studies by Holland et al. (2009), Chen et al. (2014) and Holland et al. (2015) investigate the effects of low carbon fuel standard policy.

little effect on firm's competitiveness.

2. Carbon mandates in China's national plan

China's five-year plans are a series of nationwide social and economic development initiatives including detailed five-year guidelines for social and economic development. In recent years, The Chinese government is aware of environmental issues and is concerned about the sustainable development, the five-year-plans therefore include environmental policies like controlling SO_2, COD, NO_x. To achieve the expected carbon reduction target and to curb the carbon emissions, the Chinese government starts to control carbon emissions nationwide at the beginning of the 12th Five-Year-Plan (2011–2015). Specifically, as shown in Table A1 in the Appendix, the China State Council issued a document titled "Work Plan for Controlling Greenhouse Gas Emissions during the 12th Five-Year Plan" in 2011, which specified the reduction targets and allocated them at the provincial level for the first time. In principle, the provincial reduction mandated targets were suggested based on a series of factors, such as provincial GDP growth, industrial structure, current carbon intensity and maximal potential reduction. Moreover, the plan also required that key carbon intensive industries, such as steel, electric power, coal, petroleum, chemical industries take action to reduce carbon emissions, and emissions standards should be established for the key firms in these industries.

The final mandated targets were determined after negotiation between the central government and the local government of each province (Zhang et al., 2013; Zhang, 2017). To achieve the mandated goals, it was suggested that local governments should focus on optimizing the industrial structure, improving energy efficiency and investing in low carbon technology, to reduce the carbon intensity within the province. To realize the target for controlling carbon emission, the Shanghai government issued a document titled "Interim Measures on Carbon Emission Management in Shanghai" in 2013. The government allocated special funds for energy conservation and emission reduction to support the carbon emission management within the administrative area. A series of measures were adopted, including monitoring, reporting and verifying the major emitters' carbon emission. In addition, emitters are encouraged to trade carbon emission quotas within the administrative area. More specifically, Shanghai established a carbon emission quota management system. Carbon emitters whose annual carbon emissions reach a certain standard would be subject to quota management. The government determined the carbon emission quota of each emitter by historical level of carbon emission of the unit and the characteristics of the corresponding industry. Quotas were allocated free of charge or with payment through the quota registration system. Carbon emitters under quota management (including emitters with over 10,000 tons annual carbon emissions) were required to compile their carbon emission reports for the previous year, which was verified by a third-party organization thereafter. And then the report was submitted to the Municipal Development and Reform Commission before March 31 of each year. In addition, carbon emitters under quota management were also required to set out an annual carbon emissions monitoring plan regarding the scope, ways, frequency, and the person in charge by the end of each year. The qualified emitters were encouraged to trade quotas via open bidding, transfer of agreement or other means on the carbon emissions trading platform at Shanghai Environment and Energy Exchange. The Exchange established a carbon emission trading information management system which discloses trading information such as market quotation, trading volume and transaction amount as well as relevant information that may affect major market changes. In addition, Banks and other financial institutions were encouraged to give priority to providing financial support for energy conservation and carbon reduction projects of emitters under quota management.

The top-down carbon intensity reduction mandates thus determine the stringency of regulation and can be regarded as a general measure of the strength of provincial regulation on carbon emissions. Table A1 in the Appendix shows the carbon intensity reduction mandated targets across provinces. Among these provinces, we can see Zhejiang, Tianjin, Shanghai, Jiangsu and Guangdong have the relatively high reduction mandates, Qinghai, Tibet and Hainan have the relatively low mandates on reduction. As shown in Fig. 1, overall, provinces in the eastern region have the highest reduction target, followed by the central region, the western region comes last.

To enhance the implementation of policy at the local level, the National Development and Reform Committee (NDRC) of China and other related departments were responsible for performance assessment.[2] Fig. 2 shows the relationship between the actual reductions and the mandated targets. Enforcement varied across the provinces and regions. We can see that most provinces achieved or even exceeded their targets, while only a few did not.

3. Data

3.1. Data sources and the sample

The data used in this study includes all Chinese publicly listed companies in the non-financial sector in Shanghai and Shenzhen stock markets from 2003 to 2015. We assemble this dataset from multiple sources. The detailed patent applications for Chinese listed firms are obtained from the State Intellectual Patent Office (SIPO) of China. The firm-level financial data is taken from the China Stock Market and Accounting Research (CSMAR) database, which is widely used in research on listed firms in China. By using corporate tree reported by the CSMAR database, we obtain a comprehensive list of firms' names associated with its parent company and subsidiaries. The location and industry information of subsidiaries is from National Enterprise Credit Information Publicity System (NECIPS). The data on carbon emissions is derived from China Emission Accounts and Datasets (CEADs) and Environmental Accounts of World Input-Output Database (WIOD).

First, we construct a firm-level patent database, covering the patent applications associated with all Chinese listed companies in the industries including mining, manufacturing, and public utilities sectors during the sample period. Based on the archives of the SIPO, we match and merge Chinese listed firms and their subsidiaries with those that have filed patent applications. For each firm in the merged sample, the data include patent type, application date, application number, grant date, grant number, and main International Patent Classification (IPC).

With the matched firm-level patent database from above, we further merge firms' economic fundamentals from the CSMAR database. Similar to the Compustat database from Wharton Research Data Service, CSMAR provides firm's financial information including startup year, assets, debts, labor, revenue, cash holdings, industry classification code, location and many others. The financial fundamentals play an important role in driving corporate R&D activities and productivity performance and hence are used as firm-level covariates in our empirical analysis.

Finally, we merge our firm data with the provincial reduction mandates and industrial carbon emissions by using the registered location and industry of listed firms. The final sample we have obtained include 13,641 listed company-year observations.

3.2. Variables construction

3.2.1. TFP

Several approaches can be used to estimate firm-level TFP. Specif-

[2] The assessment result showed that Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Shanghai, Jiangsu, Zhejiang, Anhui, Hubei, Guangdong, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan and Shananxi are assessed as "excellent", Heilongjiang, Fujian, Jiangxi, Shandong, Henan, Hunan, Hainan, Gansu, Qinghai and Ningxia are assessed as "good", Tibet and Xinjiang are assessed as "pass".

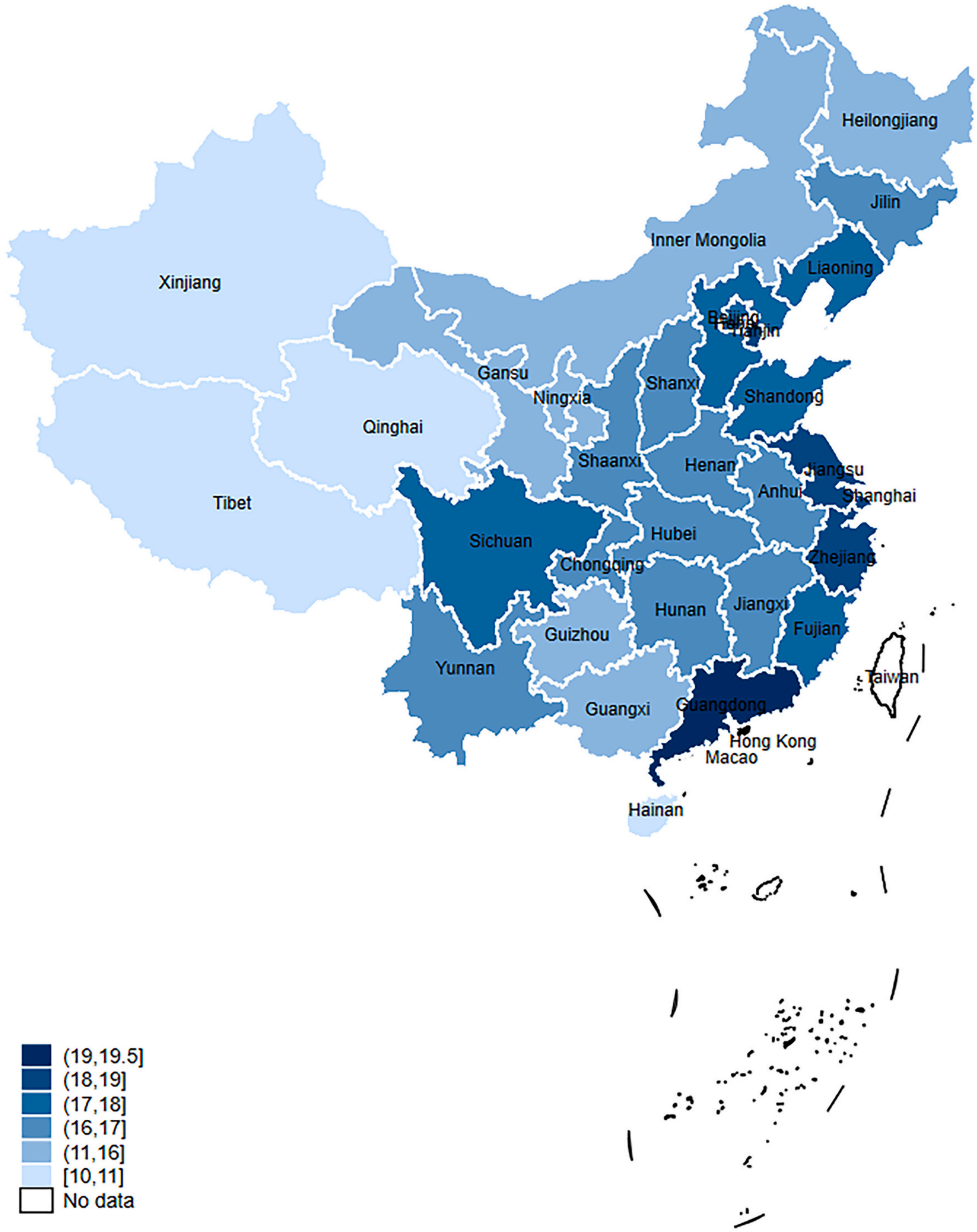

Fig. 1. Distribution of provincial carbon intensity reduction mandated targets.
Notes: The deeper the colour, the higher the provincial reduction mandated target.

ically, consider a Cobb-Douglas production function for firm i at time t.

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \tag{1}$$

where y_{it} is the logarithm of output measured by sales of goods and services; k_{it} is the logarithm of capital measured by net fixed assets; l_{it} is the logarithm of labor measured by the number of employees; and m_{it} is the logarithm of the intermediate inputs measured by cash payments for purchasing goods and receiving services. ω_{it} represents unobservable productivity, and ε_{it} is an idiosyncratic output shock.

Endogeneity issue arises when estimating Eq. (1), as the unobservable productivity shocks ω_{it} can be correlated with inputs k_{it} and l_{it}. Various methods have been proposed to tackle this issue. Olley and Pakes (1996) (hereafter, OP) use firms' investment levels to proxy for unobserved productivity shocks, but the monotonicity condition of OP requires that only observations with positive investment can be used, which limits its applications in empirical settings. To address this issue, Levinsohn and Petrin (2003) (hereafter, LP) exploit intermediate inputs as a proxy. However, Ackerberg et al. (2006) and Bond and Söderbom (2005) state that the labor coefficient cannot be consistently estimated due to the multicollinearity and identification issues in the first stage.

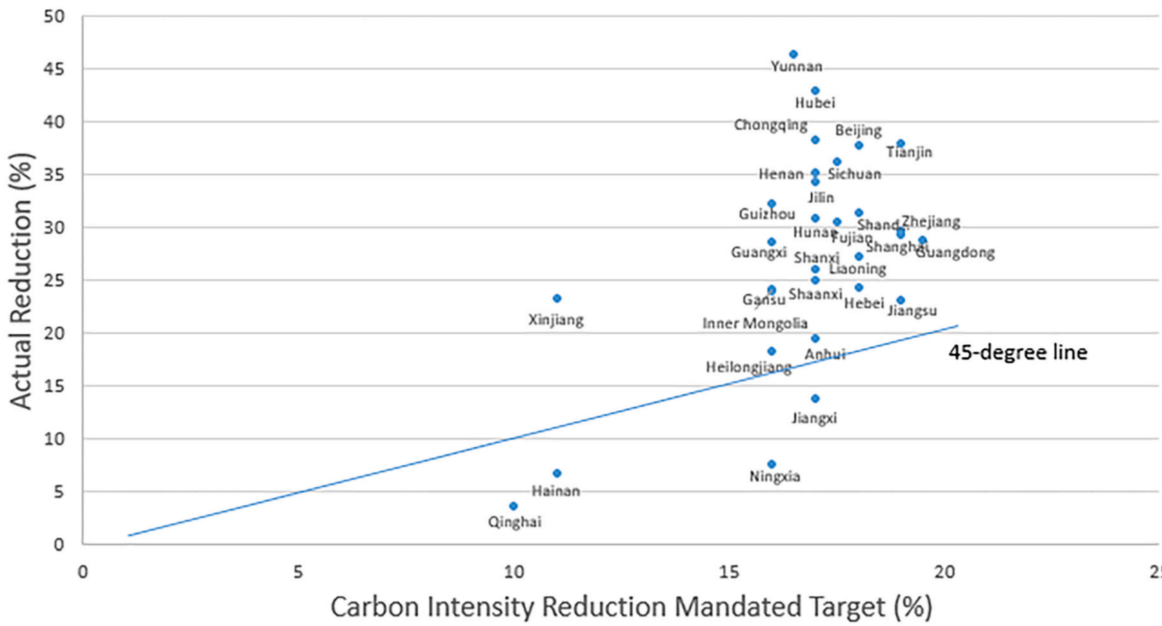

Fig. 2. Carbon intensity reduction mandated targets and actual reduction.
Notes: Small circles in the figure represent provinces. The line in the figure is the 45° line, which is not like normal 45° line due to the different scale in the x-y axis. (Source: Actual reduction is calculated from (carbon intensity in 2010- carbon intensity in 2015)/ (carbon intensity in 2010). Provincial carbon emissions are taken from China Emissions Accounts & Datasets (CEADs) and provincial GDP is taken from the China Statistical Yearbook (2011–2015).)

Ackerberg et al. (2015) (hereafter, ACF) address this issue by proposing an alternative approach that m_{it} is chosen either at the same time or after l_{it} is chosen. Therefore, we employ the LP algorithm corrected by ACF to estimate the TFP.[3] This approach has been widely used to estimate firm's productivity in the most recent empirical studies (e.g. Chor et al., 2021; Banerjee et al., 2021).

3.2.2. Low-carbon innovation

Following the previous studies (Newell et al., 1999; Johnstone et al., 2010; Calel and Dechezleprêtre, 2016; Autor et al., 2020), we use the number of patent applications, which have been successfully granted, as a proxy for firms' innovation.[4] To classify low-carbon technologies, we match each patent's main International Patent Classification (IPC) code with the IPC Green Inventory code developed by the IPC Committee of the World Intellectual Property Organization. The IPC Green Inventory classifies the so-called environmentally sound technologies in the IPC categories, as listed by the United Nations Framework Convention on Climate Change (UNFCCC). By using the definition of low-carbon patent in Cui et al. (2018), we pin down a list of IPCs associated with alternative energy production, energy conservation, and waste management.

Let $LowcarbonPat_{it}$ denote the number of low-carbon granted patent applications. Under the carbon reduction mandates, a firm could divert R&D resources to develop low-carbon technologies, which in turn may have a crowding-out effect on innovation in other areas. We use $NonLowcarbonPat_{it}$ to represent the number of patents on non-low-carbon technologies. As an alternative measure of the firm-level low-carbon innovation, we also use the ratio of low-carbon patents relative to total patents, denoted by $LowcarbonRatio_{it}$, which measures whether reduction mandates shift the direction of innovation toward low-carbon technologies. Moreover, besides carbon emission regulation, unobservable policies (e.g. innovation subsidy) may become confounding factors for a firm's decision of innovation. As suggested by the existing studies (Lanjouw and Mody, 1996; Popp, 2002; Cui et al., 2018), another advantage of using the patent ratio can further remove systematic shocks common to both low-carbon patents and total patents.

To further examine innovation heterogeneity, we exploit the variation by patent type. The SIPO of China grants two types of patents – invention patent and utility model patent. Existing research on Chinese patents indicates that invention patents represent valuable and more important innovation than utility patents (Liu and Qiu, 2016; Fang et al., 2017; Hu et al., 2017). The former is associated with inventive and new technical innovations, whereas the latter is related to technical solutions to the object's shape or structure. We therefore further classified low-carbon patents into invention and utility ones. Define $LowcarbonInvtPat_{it}$ and $LowcarbonUtyPat_{it}$ as the number of low-carbon invention patents and utility patents, respectively. Similarly, we let $LowcarbonInvtRatio_{it}$ be the ratio of low-carbon invention patents relative to all invention patents and denote $LowcarbonUtyRatio_{it}$ as the ratio of low-carbon utility patents relative to all utility patents.

3.2.3. Control variables

To control for other confounding factors that may affect firms' low-carbon innovation and TFP, we include a set of firm-level control variables. Specifically, Firm age and size are two crucial factors. Younger firms are generally considered to be more innovative, and Hsieh and Klenow (2014) find a significant effect of firm's life cycle dynamics on TFP. Firm age (*Age*) is measured by the difference between the current year and startup year. Larger firms tend to have larger inputs and outputs and would have more resources devoted to innovation. We measure firm size (*Size*) by natural logarithm of the book value of total assets (Yuan). Moreover, financial situation can also influence firm's TFP and innovation activities (Aghion et al., 2010, 2012; Duval et al., 2020). Firms that encounter financial constraints are less likely to invest in long-term and risky innovation activities. To capture this, we use leverage and cash holdings to measure a firm's financial situation. The former is represented as the ratio of the firm's total debts to its total assets (*Leverage*), while the latter is the ratio of the net increase in cash and cash equivalents to current liabilities (*Cash*). Finally, we measure

[3] We also use LP algorithm and the approach of Wooldridge (2009) to estimate TFP for robust check.

[4] Generally, there is a time lag of 1 to 3 years between the filing and the publishing of granted patent applications. By matching patent applications and granted patents, we use the patent applications which have been successfully granted later as the proxy for firms' innovation.

firms' growth opportunities with *Tobin's Q*, which is calculated as the sum of the market value of tradable shares and the book value of non-tradable shares and total liabilities divided by the book value of total assets.

3.3. Summary statistics

Overall, we have a sample of 2389 listed companies with 42,858 subsidiaries in 74 two-digit industries across 31 province-level regions from 2003 to 2015. The final merged data has 13,641 listed company-by-year observations. Table 1 shows the summary statistics for the main variables used in this study. The mean TFP of the Chinese publicly listed firms in the sample is 2.874 with the standard deviation 0.340, which means that TFP differs significantly across firms. On average, a firm has about 37 total granted patent applications, among which 0.897 patents are associated with low-carbon technologies (0.162 invention patents and 0.735 utility patents). The mean low-carbon patents ratio is 0.019, the corresponding low-carbon invention ratio is 0.008 and utility ratio is 0.022. The average firm size is 21.927, leverage is 0.479, cash is 0.097, age is 2.497 and Tobin's Q is 1.981. The average provincial mandated target is 16.452%, and the mean industrial carbon emissions (2003–2010 average) is 102.068 million tons.

4. Empirical strategy

If we only consider the parent company of listed firms, assuming it operates in one province and covers one industry, we can apply a difference-in-difference-in-differences (DDD) strategy. In other words, we combine three types of variation: the time variation (i.e., before and after the start of the 12th Five-Year Plan), the provincial variation (i.e., provinces with high mandates on carbon reduction versus provinces with low mandates), and the industrial variation (i.e., more carbon intensive versus less carbon intensive industries). We can estimate the following regression:

$$Y_{ijpt} = \beta^* ln\left(Target_p\right)^* Post_t^* ln\left(CO_{2\,j}\right) + \boldsymbol{\gamma}'\boldsymbol{Z_{it}} + \lambda_i + \delta_{jt} + \eta_{pt} + \varepsilon_{ijpt} \tag{2}$$

where Y_{ijpt} represents the firm *i*'s TFP or granted patent applications in 2-digit industry *j*, province *p* and year *t*.[5] $Target_p$ is the provincial mandated target on carbon reduction for province *p*; $Post_t$ is a dummy variable which equals to 0 for 2003–2010 and 1 for 2011–2015; CO_{2j} is the average CO_2 emissions from 2003 to 2010 for each industry *j*. $\boldsymbol{Z_{it}}$ is a set of firm-level control variables including age, size, cash, leverage and Tobin's Q. We control for the 2-digit industry-year (δ_{jt}) and province-year (η_{pt}) fixed effects, which absorb the time-variant industrial and provincial confounding unobservable influencing firm's TFP or patent. We also control for the firm-level fixed effect (λ_i) capturing the firm-level heterogeneity, and ε_{ijpt} is an error term.

However, the above specification may not be accurate. A large listed company can have multiple subsidiaries. In any given year, a firm in China can operate in multiple provinces (on average, one listed firm in the sample runs their business in 3 provinces each year), and operate in multiple industries (on average, one listed firm in the sample covers 4 industries each year). Depending on the industry, region and time, these subsidiaries can have different treatment shocks. The simple case as described in eq. (2) therefore cannot reflect the level of carbon regulation a firm faces in reality, which can cause the biased estimation. Thus, we turn to a more nuanced empirical model that incorporates the facts.

Following the approach proposed by Hanna (2010),[6] we construct the alternative measure of the mandates treatment—exposure to carbon intensity control (*Exposure*)[7]:

$$Exposure_{it} = \frac{1}{N_{i,t}}\sum\nolimits_{n=1}^{N_{i,t}}\left(ln\left(Target_{np}\right) \times ln\left(CO_{2\,nj}\right) \times Post_t\right) \tag{3}$$

where $Exposure_{it}$ represents the listed company *i*'s exposure to the mandates in year *t*. $N_{i,t}$ is the total number of subsidiaries of listed company *i* in year *t*; $Target_{np}$ is the carbon reduction mandated target in province *p* where the subsidiary *n* is located. $CO_{2\,n\,j}$ is the average CO_2 emissions from 2003 to 2010 for the 2-digit industry *j* of the subsidiary *n*; $Post_t$ is defined as before. In short, *Exposure* variable measures listed company's exposure to the mandates as the average of all its subsidiaries' exposures. A larger value of *Exposure* implies that the listed company faces a higher degree of pressure on carbon intensity control.

We then specify the baseline empirical model as follows:

$$Y_{ijpt} = \beta^* Exposure_{it} + \boldsymbol{\gamma}'\boldsymbol{Z_{it}} + \lambda_i + \delta_{jt} + \eta_{pt} + \varepsilon_{ijrt} \tag{4}$$

Table 1
Summary statistics.

	Obs	Mean	S.D.	Min	Max
Panel A: Firm-level					
Size	13,641	21.927	1.278	16.704	28.509
Leverage	13,641	0.479	1.210	0.007	96.959
Cash	13,641	0.097	1.584	−70.715	64.185
Age	13,641	2.497	0.471	0	3.871
Tobin's Q	13,325	1.981	1.742	0.153	118.255
TFP	13,609	2.874	0.340	−0.675	5.442
LowcarbonPat	13,641	0.897	5.108	0	173
NonLowcarbonPat	13,631	36.622	189.1119	0	12,384
LowcarbonRatio	13,631	0.019	0.082	0	1
LowcarbonInvtPat	13,641	0.162	2.000	0	105
LowcarbonUtyPat	13,641	0.735	3.908	0	163
LowcarbonInvtRatio	13,637	0.008	0.063	0	1
LowcarbonUtyRatio	13,633	0.022	0.0092	0	1
Panel B: Province level					
Provincial mandated target (%)	31	16.452	2.541	10	19.5
Panel C: Industry level					
Industry CO_2 emissions (2003–2010 average) (10^6 tons)	74	102.068	388.987	0.127	2990.162

Notes: this table reports the main variables used in this study. *Size* is measured by natural logarithm of the book value of total assets. *Age* is measured by natural logarithm of the difference between the current year and startup year. *Leverage* is represented as the ratio of the firm's total debts to its total assets. *Cash* is the ratio of the net increase in cash and cash equivalents to current liabilities. *Tobin's Q* is calculated as the sum of the market value of tradable shares and the book value of non-tradable shares and total liabilities divided by the book value of total assets. TFP is calculated as LP algorithm corrected by ACF.

[5] As discussed by Ederington and Minier (2003), polluter lobbying groups may adversely influence policymaking, thus endogeneity problem can arise. This is very unlikely in our context, the carbon reduction targets were negotiated between the central government and the local governments and the mandated goals were predetermined by the central government at the beginning of the 12th FYP, which was out of firm's control. This specific setting rules out the concerns of the reverse causation problem. Some recent studies also use the mandated target in pollution reduction as plausibly exogenous environmental regulation (Wu et al., 2017; Maurel and Pernet, 2020).

[6] Hanna (2010) measures multi-plant firms' exposure to the local regulation by considering whether an affiliated plant is located in non-attainment counties and belongs to heavily polluting industry under the Clean Air Acts implemented by the US Environmental Protection Agency.

[7] Assuming one listed company has 5 subsidiaries in different industries and regions, then the exposure of this listed company can be calculated as: $Exposure_{it} = \frac{1}{5}\sum_{n=1}^{5}\left(ln\left(Target_{np}\right) \times ln\left(CO_{2\,nj}\right) \times Post_t\right)$, where $Target_{np}$ is mandated target of the corresponding subsidiary *n*'s province *p*, $CO_{2\,nj}$ is the carbon emission of the corresponding subsidiary *n*'s industry *j*. $Post_t$ is a dummy variable which equals to 0 for 2003–2010 and 1 for 2011–2015. We construct the *Exposure_ETS* in the similar way.

where Y_{ijrt} represents the listed company i's TFP or granted patent applications in year t.[8] $Exposure_{ijpt}$ is aforementioned regulation variable; Similarly, $\boldsymbol{Z}$ is a set of firm-level control variables including age, size, cash, leverage and Tobin's Q. We control for the 2-digit industry-year (δ_{jt}), province-year (η_{rt}) fixed effects, and firm-level fixed effect (λ_i), and ε_{ijrt} is an error term. Overall, we use the registered industry and location information of the listed companies (which is the same as the parent company) to control for industrial fixed effects. We then use subsidiaries information to construct the policy exposure variable.

To further check the validity of the empirical strategy, we conduct a battery of sensitivity tests. These include using alternative measures of firm's TFP, controlling for firm-level environmental policy, carbon emissions trading scheme, the innovation subsidy, clustering standard errors at the industry-province level.

5. Results

In this section, we start with the baseline results and then conduct a series of robustness checks to mitigate the endogeneity concerns from potential confounding factors. The heterogeneous effects are also discussed. We finally explore the firm's response to carbon reduction mandates through which the mandates influence the firm's TFP.

5.1. Baseline results

Table 2 reports the estimated effects of exposure to carbon reduction mandates on firm's innovation and TFP. In all columns, we control for firm fixed effects, 2-digit industry-year effects and province-year effects to absorb confounding unobservable factors at the firm, industry and province levels. These fixed effects help to control for the industrial and regional environmental and energy policy shocks like regional pilot carbon emissions trading and provincial targets of reducing energy intensity. Robust standard errors in the parentheses are clustered at the firm level.

Columns (1) and (3) of Table 2 show the estimated effects of carbon mandates on low-carbon patents. The estimated coefficient of interest is 0.009 and statistically significant at the 10% for the number of low-carbon patents, whereas the estimated coefficient of *Exposure* in column (3) is 0.002 and statistically significant at the 1%, implying that one unit increase in exposure to the mandates leads to 0.9% (e^0.009–1 ≈ 0.9%) in the low-carbon granted patent applications and 0.2% increase in the low-carbon patent ratio. In column (2), we find no significant crowding-out effect of the mandates on the firm's innovation in other areas.

Moreover, in columns (1)–(3), we can clearly see the significant positive effect of firm's size on firm's innovation, suggesting that firm size plays an important role on innovation. As shown in column (4), we do not observe significant negative effect of mandates on firm's TFP. Overall, we find that carbon mandates significantly boost the firm's innovation in low-carbon technologies and have no significant crowding-out effect on firm's innovation in other areas. Under such mandates, firms tend to have directed technical change toward low-carbon technologies, while firm TFP is not affected by the mandates.

We further replace "Post" with a set of year dummies to investigate the parallel pre-trends. As shown in Fig. A1 in the Appendix, we do not find any significant shock on firm's low-carbon innovation and TFP in the pre-policy period. In other words, the parallel pre-trends hold for firm's low-carbon innovation and TFP, further confirming the validity of our baseline results.

5.2. Heterogeneous effects

In addition to the average effects, in this section, we further examine whether our main results vary across firms with different ownership and patent type.

First, we divide the sample into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs) based on the firm's largest ultimate share holder of the firm and run the regression (4). Table 3 reports the estimated results. In column (1), for the non-SOEs, we can see the coefficient of *Exposure* is statistically significant at the 10% level, while the coefficient of *Exposure* is not significant for the SOEs. These suggest that the carbon reduction mandates mainly boost the non-SOEs' low-carbon innovation. From Column (3), the coefficient of *Exposure* is statistically significant at the 5% for the SOEs whereas the coefficient of *Exposure* for non-SOEs is not significant, indicating that the mandates mainly shift the SOEs' direction of innovation toward low-carbon technologies. In addition, the heterogeneity analysis by ownership still shows little evidence of the effects of mandates on innovation in other areas or firm's TFP.

Moreover, we show the heterogeneity by patent type. As mentioned before, we divide the patent type into invention patent and utility model patent. Invention patents represent valuable and more important innovation than utility patents. The former is associated with inventive and new technical innovations, whereas the latter is related to technical solutions to the object's shape or structure. As shown in Table 4, in columns (2) and (4), the coefficients of Exposure are statistically significant at the 10% and 1% respectively, providing the evidence that the mandates mainly stimulate the low-carbon utility model patents. Whereas the estimated coefficients from columns (1) and (3) show that the low-carbon invention patents are not significantly affected. These facts show that under the carbon reduction mandates, the quality of firm's low-carbon innovation is not as good as we may expect.

5.3. Placebo tests on confounding policies

A. Firm-level environmental policies

The firm-level environmental pressure (e.g. air quality regulation) may induce firms to conduct R&D activities in low-carbon technologies. In 2004, China Ministry of Ecology and Environment (formerly, Ministry of Environmental Protection) launched a Clean Production Audit (CPA) program to promote cleaner production and reduce pollution through the improvement of technology design, the adoption of clean energy, and the installation of the cleanest available technology or equipment. The provincial governments announced a list of companies that mandatorily participating in the CPA program within their jurisdiction since 2004. To address this concern, we match and merge the listed firms with those included in the CPA program. We measure this regulation by using a binary indicator denoted by *CPA_program*. It equals one if the firm *i* mandatorily joined the CPA program in year *t*, and zero otherwise.

On the other hand, the Ministry of Environmental Protection also launched a Key Pollution Monitoring (KPM) program to get direct access to the pollution discharge information of key industrial pollution sources and centralized pollution control facilities in 2006. The Ministry of Environmental Protection and provincial government announced a list of key polluting enterprises under national and provincial monitoring each year since 2006. To mitigate this concern, we match and merge the listed firms with those included in the KPM program. Similarly, we measure this firm-level regulation by using a binary indicator denoted by *KPM_program*. It equals one if the firm i mandatorily joins the CPM program in year t, and zero otherwise.

[8] Following Cui et al. (2018) and Kong et al. (2020), throughout the paper, we use log $(1 + x)$ to avoid the problem of zeros, where x is the number of patents. We have obtained similar results when using the number of patents in the Poisson model, which are available from the authors upon request.

Table 2
Baseline results.

Variables	*LowcarbonPat* (1)	*NonLowcarbonPat* (2)	*LowcarbonRatio* (3)	*TFP* (4)
Exposure	0.009*	−0.007	0.002***	−0.002
	(0.005)	(0.009)	(0.001)	(0.025)
Size	0.159***	0.466***	0.004*	−0.008
	(0.020)	(0.034)	(0.002)	(0.010)
Age	0.019	−0.011	0.002	−0.019
	(0.062)	(0.100)	(0.005)	(0.024)
Tobin's Q	−0.011	−0.019***	−0.001	0.018***
	(0.005)	(0.007)	(0.001)	(0.004)
Cash	0.001	−0.018***	−0.0004	0.008***
	(0.001)	(0.004)	(0.0002)	(0.002)
Leverage	0.011*	0.019**	0.001	−0.036***
	(0.006)	(0.008)	(0.001)	(0.007)
Constant	−3.349***	−7.917***	−0.079*	3.092***
	(0.449)	(0.765)	(0.046)	(0.222)
Observations	12,857	12,848	12,848	12,828
Firm FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.604	0.752	0.347	0.685

Notes: *LowcarbonPat* refers to the low-carbon granted patent applications, *NonLowcarbonPat* represents the granted patent applications in other areas, and *LowcarbonRatio* is the ratio of low-carbon patents relative to total patents. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * significant at the 1%, 5%, and 10% level, respectively.

Table 3
Heterogeneity by ownership.

	LowcarbonPat (1)	*NonLowcarbonPat* (2)	*LowcarbonRatio* (3)	*TFP* (4)
SOEs:				
Exposure	0.002	0.016	0.002**	−0.005
	(0.008)	(0.140)	(0.001)	(0.004)
Observations	6040	6033	6033	6032
Adjusted R-squared	0.621	0.791	0.252	0.708
Non-SOEs:				
Exposure	0.013*	−0.091	0.001	−0.0005
	(0.007)	(0.011)	(0.001)	(0.004)
Observations	6512	6510	6510	6492
Adjusted R-squared	0.611	0.717	0.460	0.710
Firm Attributes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes

Notes: *LowcarbonPat* refers to the low-carbon granted applications, *NonLowcarbonPat* represents the granted patent applications in other areas, and *LowcarbonRatio* is the ratio of low-carbon patents relative to total patents. SOEs represent the state-owned firms, and Non-SOEs represent the non-state-owned firms. Firm attributes include firm's size, age, leverage, cash and Tobin's Q. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * significant at the 1%, 5%, and 10% level, respectively.

Panel A and B of Table 5 report the results, respectively.[9] Panel A of Table 5 presents the results when including the *CPA_program* while Panel B reports the results when we include the *KPM_program* in the regression. The results are quite similar. in column (1), the positive coefficient of *Exposure* in Panel A is statistically significant at the 5% level while the corresponding coefficient in Panel B is similarly statistically significant at the 5% level. In column (3), both panels show the same results. Moreover, in all columns, the coefficients of *CPA_program* or *KPM_program* are not significant, suggesting that firm-level environmental policies, either CPA or KPM, has no significant effect on innovation or TFP in our case.

[9] As the environmental research sub-database of the CSMAR database provide the data related to CPA and KPM programs starting from 2008, the matched sample covers the period 2008–2015, leading to a substantial drop in sample size. We also drop the observations with KPM or CPA program and get similar results, which are available from the authors upon requests.

Table 4
Heterogeneity by patent type.

	LowcarbonInvt Pat (1)	*LowcarbonUty Pat* (2)	*LowcarbonInvt Ratio* (3)	*LowcarbonUty Ratio* (4)
Exposure	0.002	0.009*	−0.0004	0.002***
	(0.003)	(0.005)	(0.001)	(0.0009)
Observations	12,857	12,857	12,854	12,850
Adjusted R-squared	0.471	0.580	0.216	0.319
Firm Attributes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes

Notes: *LowcarbonInvtPat* refers to the low-carbon granted invention patent applications, *LowcarbonUtyPat* represents the granted utility patent applications, *LowcarbonInvtRatio* is the ratio of low-carbon invention patents relative to total invention patents, *LowcarbonUtyRatio* is the ratio of low-carbon utility patents relative to total utility patents. Firm attributes include firm's size, age, leverage, cash and Tobin's Q. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * significant at the 1%, 5%, and 10% level, respectively.

B. Regional pilot carbon emissions trading policy

Although we control the industry-year and province-year fixed effects which could rule out potential confounding factors at the industrial and provincial levels, some contemporary energy and environmental policies may bias the estimated effect of the mandates. Particularly, the pilot carbon emissions trading scheme (ETS) is the biggest threat to the identification. In 2011, the National Development and Reform Commission (NDRC) announced that Shanghai, Beijing, Guangdong, Tianjin,

Table 5
Placebo tests on confounding policies.

Variables	*LowcarbonPat*	*NonLowcarbonPat*	*LowcarbonRatio*	*TFP*
	(1)	(2)	(3)	(4)
Panel A: control for CPA program				
Exposure	0.018**	−0.004	0.003**	−0.002
	(0.008)	(0.013)	(0.001)	(0.004)
CPA_program	−0.003	0.004	−0.005	0.001
	(0.025)	(0.044)	(0.005)	(0.009)
Adjusted R-squared	0.682	0.781	0.420	0.747
Observations	5873	5870	5870	5863
Panel B: control for KPM program				
Exposure	0.018**	−0.004	0.003**	−0.002
	(0.008)	(0.013)	(0.001)	(0.004)
KPM_program	−0.008	0.095	−0.001	0.017
	(0.035)	(0.076)	(0.006)	(0.014)
Adjusted R-squared	0.682	0.781	0.420	0.747
Observations	5873	5870	5870	5863
Panel C: control for pilot carbon emissions trading				
Exposure	0.011**	−0.006	0.002**	−0.003
	(0.005)	(0.009)	(0.001)	(0.003)
Exposure_ETS	−0.021	−0.018	0.0004	0.013**
	(0.014)	(0.023)	(0.002)	(0.007)
Adjusted R-squared	0.604	0.752	0.346	0.685
Observations	12,857	12,857	12,848	12,828
Firm attributes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes

Notes: *LowcarbonPat* refers to the low-carbon granted patent applications, *NonLowcarbonPat* represents the granted patent applications in other areas, and *LowcarbonRatio* is the ratio of low-carbon patents relative to total patents. Firm attributes include firm's size, age, leverage, cash and Tobin's Q. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * significant at the 1%, 5%, and 10% level, respectively.

Hubei, Chongqing and Shenzhen were selected as the regional carbon emissions trading scheme (ETS) pilots. To further mitigate this concern, we take the pilot (ETS) into consideration. Following the way of constructing *Exposure* variable, we construct the variable *Exposure_ETS* to measure the firm's exposure to regional ETS:

$$Exposure\_ETS_{it} = \frac{1}{N_{i,t}}\sum_{n=1}^{N_{i,t}}\left(ETS_{np}*ln\left(CO_{2\ nj}\right)*Post_t\right) \tag{5}$$

where $Exposure\_ETS_{it}$ represents the parent firm i's exposure to carbon emissions trading in year t. $N_{i,t}$ is the number of subsidiaries of firm i in year t; ETS_{np} refers to the binary indicators for pilot region p where the subsidiary n is located. $CO_{2\ n\ j}$ is the average CO_2 emissions from 2003 to 2010 for industry j of subsidiary n; $Post_t$ is a dummy variable equal to 0 for 2003–2010 and 1 for 2011–2015.

We include *Exposure_ETS* in the regression and obtain the corresponding estimated results, as shown in Panel C of Table 5. Overall, including *Exposure_ETS* variable does not change our main conclusions. Specifically, the coefficients of Exposure in columns (1) and (3) are similar to the baseline results and are both statistically significant at the 5% level, the coefficients of *Exposure_ETS* are not significant, suggesting that the innovation in low-carbon technologies are mainly driven by the carbon reduction mandates instead of ETS. Moreover, in column (4), the positive coefficient of *Exposure_ETS* is statistically significant at the 5% level, indicating ETS has a positive effect on the firm's TFP.

5.4. Robustness checks

In this section, we conduct a battery of robustness checks for our results. In all models in the section, we include firm attributes (age, size, cash, leverage and Tobin's Q) and control for province-year fixed effects, industry-year fixed effects and firm fixed effects in all analyses.

Firstly, we take into account the confounding effects of government subsidy. The Chinese governments may offer subsidies for firms conducting research and development in a list of selected high technologies, such as low-carbon technologies. The CSMAR database has the firm-level subsidy data, which reports subsidy amount and subsidy reasons (e.g. subsidy for granted patents). To address this confounding policy, we obtain the corresponding subsidy dataset by retrieving those related to patent applications and granting and mitigate the subsidy effects in two ways. In Panel A of Table A2 in the Appendix, we drop the firms that have received subsidies for patents. The sample size drops substantially accordingly, but the coefficients of interest are similar and still significant. For the low-carbon patents, the estimated coefficient is 0.011 and significant at the 5% level, which is more significant compared with the baseline results. In column (3), the estimated effect of *Exposure* is 0.003 and significant at the 5% level, indicating that 1 unit increase in exposure to the mandates increase 0.3% in low-carbon patent ratio. Panel B reports the results when the *Innovation_subsidy* (flow) (subsidy received within one year) is included as one additional control variable in the regression. The estimated coefficients of *Exposure* do not change and the estimated coefficient in column (1) is significant at the 5% level. In addition, we can clearly see the significant boost effect of the subsidy on the innovation in other areas (1% increase in innovation subsidy can lead to 0.8% increase in granted patent application in other areas), as shown in column (2). Given that accumulated innovation subsidies may persistently influence firm's innovation performance, we further include *Innovation_subsidy* (stock), which is measured by accumulated innovation subsidies in the previous years. Panel C reports the similar estimated results. The significance level and coefficients of *Expsoure* are similar to the baseline results. Overall, the main conclusion still holds.

Secondly, to verify the robustness of our results under different TFP measures, we estimate firm's TFP by using alternative methods. Specifically, we construct two alternative TFP measures—*TFP1* measured by LP algorithm and *TFP2* measured by Wooldridge (2009).[10] Table A3 in the Appendix reports the estimated coefficients. In all columns, the coefficients of *Expsoure* are insignificantly negative, which are consistent with the finding in baseline results, further supporting that carbon reduction mandates do not harm the firm's TFP.

Third, although we cluster the robust standard errors at the firm level, the unobserved components in firm's innovation or TFP within an industry in one region may also be correlated. To verify whether our main findings are robust after considering these correlations, we use heteroscedastic robust standard errors clustered at the industry-province level and report the results in Table A4. Clearly, our results are still robust.

In addition, to alleviate concern about the existing trend, we further control linear and quadratic polynomials of time trend. As shown in

[10] LP algorithm relies on intermediate inputs as a proxy for unobserved productivity shocks. Wooldridge (2009) proposes a novel estimation setting and shows how to obtain LP estimator within a system GMM econometric framework.

Table A5, even considering the linear or quadratic polynomials of time trend, our results are very similar to the baseline estimates.

Furthermore, we also include additional control variables (i.e., firm-level trade value and R&D investment) to test the robustness of our baseline results. More specifically, we match the sample with customs data maintained by China's General Administration of Customs and obtain the listed company's annual trade (export and import) value. We further extract the firm-level R&D investment from CSMAR database and merge the R&D data with our sample. Table A6 reports the results. We do not find any significant effect of firm-level trade and R&D investment on the firm's low-carbon innovation and TFP. And the coefficients of *Expsoure* are very similar to the baseline results.

Lastly, as the carbon reduction may not be random, our estimate could suffer from sample selection bias. To address this concern, we follow the approach proposed by Gentzkow (2006) and Chen et al. (2018).[11] In this paper, we use the interactions between determinants of provincial carbon mandates measured in the pre-treatment period and a third-order polynomial in time, namely, $Z_c \times f(t)$. More specifically, these factors (i.e., Z_c) include *Energy Consumption* (annual average provincial energy consumption 2006–2010, 10,000 ton), *Carbon Emissions* (annual average provincial carbon emissions 2006–2010, 1000,000 ton), *GDP* (annual average provincial GDP 2006–2010, 100,000,000 Yuan), *Industrial Structure* (annual average provincial secondary sector GDP share 2006–2010 (%)), *Population* (annual average provincial population 2006–2010, 10,000 persons) and *Forest Area* (annual average provincial forest area 2006–2010, 10,000 ha). Table A7 reports the results. We still find similar results, further confirming the validity of baseline results.

6. How do firms respond to the mitigation mandate?

In this section, we discuss how firms respond to the exposure to mandate. He et al. (2020) discuss the responses of firms to environmental regulation, including adjustment in labor and capital input, investment in abatement equipment and reduction in emissions, which therefore affects the firm's TFP. Moreover, Lanoie et al. (2011) and Franco and Marin (2017) highlight the indirect effect of environmental regulation via innovation on productivity. We examine the channels related in spirit to these studies through which the mandates affect firms' TFP.

Given that the accumulated low-carbon patents can influence the firm's performance, we therefore measure the firm's patent by constructing two indicators, one is *LowcarbonPat_flow*, measured by the low-carbon granted applications within one year; the other is *LowcarbonPat_stock*, the accumulated low-carbon patents.[12] We use one-year lagged *LowcarbonPat_flow* and *LowcarbonPat_stock* in the following regressions.

First, Table 6 reports the estimated results of exposure to mandate and low-carbon innovation on a set of firm's inputs and outputs. As the energy consumption is a major source of carbon emissions, we take into account the firm's energy intensity measured by energy consumption per unit of output value.[13] From columns (1)–(2), based on the limited sample, we still find the significant negative effect of exposure to mandate on firm's energy intensity and the induced low-carbon innovation does not have the significant effect on the energy intensity. From columns (3) and (4), we find statistically insignificant effect of exposure to mandate on employees and significant positive effect of low-carbon innovation on employees. In columns (5)–(6), we can clearly see that the coefficient of *Exposure* is 0.021 and significant at the 1% level, suggesting that the larger exposure to carbon intensity control leads to an increase in fixed assets. This finding is consistent with the results of He et al. (2020) showing that upstream polluting firms own significantly higher levels of capital assets due to the tighter environmental regulation. In addition, the significant coefficients of *LowcarbonPat_flow* (lagged) and *LowcarbonPat_stock* (lagged) suggest that the induced Low-carbon innovation helps to expand the fixed assets of the firm, as shown in columns (7) and (8) of the table. We do not find any significant effect of the mandates on firm's intermediate input.

As both labor and capital inputs have been increased through the induced innovation, it finally significantly boosts the firm's output. As shown in columns (9) and (10), 1% increase in *LowcarbonPat_flow* can lead to 0.031% in the output and 1% increase in *LowcarbonPat_stock* will lead to 0.033% in the output.

We further explore the effects of exposure to mandate on firm's input substitution in Table 7. We measure substitution between labor and energy by *Labor/Energy ratio* (employees/energy consumption), and substitution between capital and energy by *Capital/Energy ratio* (fixed assets/energy consumption). From columns (1)–(4), we do not observe any significant input substitution induced by mandate. We also do not find any significant effect of low-carbon patent, either measured by patent flow or patent stock, on firm's input substitution. In columns (5) and (6), the significant positive coefficients of exposure suggest that exposure to mandate significantly increases firm's Capital/Labor ratio, which is measured by fixed assets/employees, showing that firms tend to update production equipment and invest more in advanced abatement equipment to cope with tighter carbon emissions control. Therefore, we conclude that the induced innovation does not affect the energy productivity associated with labor or capital inputs.

Finally, we examine the effects of low-carbon innovation induced by the mandate on firm's productivity. Motivated by the above findings, we further include labor productivity (output value/employees) and capital productivity (output value/ fixed assets). To alleviate reverse causality and simultaneity, as suggested by previous studies (Dabla-Norris et al., 2012; Franco and Marin, 2017), we also employ the average *LowcarbonPat_flow* and *LowcarbonPat_stock* of peer firms in the same industry in the same region per year as an instrument variable (IV).[14] As shown in Table 8, Panel A reports the results of using lagged low-carbon patent whereas Panel B shows the results of using IV.[15]

From Panel A, in columns (1) and (2), the estimated coefficients of *LowcarbonPat_flow* (lagged) and *LowcarbonPat_stock* (lagged) are positive but not significant, suggesting that the induced low-carbon innovation does not significantly improve firm productivity measured by TFP.

[11] Gentzkow (2006) use interactions between key county-level observables in a base year and a fourth-order polynomial in time, which controls flexibly for differences in the time path of the dependent variables whose correlation with television is driven by the endogenous pattern of television's introduction. Similarly, due to the non-random selection of (two control zone) TCZ and non-TCZ cities, Chen et al. (2018) use the interactions between the determinants of TCZ selection measured in the pre-treatment period and a third-order polynomial in time.

[12] We calculate the *LowcarbonPat_stock* by using the perpetual inventory method, i.e., $KP_t = P_t + (1 - \delta)KP_{t-1}$ and $KP_1 = \frac{P_1}{g+\delta}$, where *KP* represents the *LowcarbonPat_stock*, *P* is granted patent applications, *g* is the average growth rate of granted patent applications and δ is the depreciation rate, which is usually assumed to be 15% (Hall and Mairesse, 1995; Lach, 1995; Bretschger et al., 2017).

[13] The listed firms in China disclosed their environmental information since 2008. We merge the sample with those which disclosed their energy consumption. With limited sample size compared to the full sample in the main analysis, it does not allow us to include the province-year and industry-year fixed effects. We instead include province, industry and year fixed effects.

[14] The observation from the firm itself is removed when computing the average, which leads to the loss of 3139 and 3347 observations respectively due to industry-province cells with only a single firm.

[15] From Panel B, in all columns, Kleibergen-Paap rk LM statistics indicates that we can reject the null hypothesis that the model is unidentified. We also report the Cragg-Donald Wald F statistics under the assumption of homoskedasticity and the heteroskedasticity-robust Kleibergen-Paap rk Wald F statistics. Both values suggest we can reject the null hypothesis of weak instrument. The results verify the validity of the IV.

Table 6
Effects of the mandates and low-carbon innovation on firm's input and output.

Variables	Energy Intensity (1)	Energy Intensity (2)	Employee (3)	Employee (4)	Fixed assets (5)	Fixed assets (6)	Intermediate Input (7)	Intermediate Input (8)	Output (9)	Output (10)
Exposure	−0.289*	−0.293*	−0.0005	−0.0007	0.021***	0.021***	−0.003	−0.003	−0.005	−0.005
	(0.154)	(0.151)	(0.007)	(0.006)	(0.005)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)
LowcarbonPat_flow	0.178		0.028**		0.042***		0.021		0.031***	
(lagged)	(0.116)		(0.014)		(0.012)		(0.013)		(0.012)	
LowcarbonPat_stock		0.256		0.053**		0.050***		0.019		0.033**
(lagged)		(0.162)		(0.023)		(0.017)		(0.016)		(0.014)
Observations	126	126	9521	9521	9530	9530	9529	9529	9526	9526
R-squared	0.521	0.530	0.932	0.932	0.963	0.963	0.972	0.972	0.977	0.977
Firm attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes								
Industry FE	Yes	Yes								
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Firm attributes include firm's size, age, leverage, cash and Tobin's Q. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * significant at the 1%, 5%, and 10% level, respectively. For energy intensity, with limited sample size compared to the full sample in the main analysis, it does not allow us to include the province-year and industry-year fixed effects. We instead include province, industry and year fixed effects.

Table 7
Effects of the mandates and low carbon innovation on firm's input substitution.

	Labor/Energy ratio (1)	*Labor/Energy ratio* (2)	*Capital/Energy ratio* (3)	*Capital/Energy ratio* (4)	*Capital/Labor ratio* (8)	*Capital/Labor ratio* (9)
Exposure	0.019	0.022	−0.0001	0.001	0.021**	0.022**
	(0.020)	(0.021)	(0.012)	(0.013)	(0.010)	(0.010)
LowcarbonPat_flow	0.036		−0.054		0.013	
(lagged)	(0.031)		(0.059)		(0.020)	
LowcarbonPat_Stock		−0.033		−0.078		−0.003
(lagged)		(0.075)		(0.077)		(0.028)
R-squared	0.371	0.370	0.725	0.729	0.855	0.855
Firm attributes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Firm attributes include firm's size, age, leverage, cash and Tobin's Q. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * significant at the 1%, 5%, and 10% level, respectively. For Labro/Energy ratio and Capital/Energy ratio, with limited sample size compared to the full sample in the main analysis, it does not allow us to include the province-year and industry-year fixed effects. We instead include province, industry and year fixed effects. For Capital/Labor ratio we include the province-year and industry-year fixed effects. All models have controlled for firm fixed effects.

Columns (3) and (4) show the similar results, i.e., the induced low-carbon patent does not significantly influence the labor productivity. However, the results from columns (5) and (6) show that exposure to mandate significantly lowers the firm's capital productivity. This should be attributed to the significant increase in the fixed assets for carbon mitigation due to the mandate. We also find that the induced innovation does not improve either labor or capital productivity. This is consistent with our argument in Table 6 that innovation induced from exposure to mandate serves to expand the size of both labor and capital inputs, in order to mitigate the reduction in inputs that firms have used for fulfilling the mandate requirement. The results from Panel B with IV estimation confirm our results.

Overall, although firms have to devote resources to meet the carbon intensity control target, firms respond to the policy shock from two directions. It will increase the capital inputs as technologies are required to mitigate carbon emissions on the one hand, and induce firms to conduct more innovations on the other hand. The induced low-carbon innovation stimulates the firm's output. This may explain why firm competitiveness measured by TFP is not affected by the mandate policy. Despite the fact that the low-carbon innovation cannot result in net productivity gains, thereby not enhancing the competitiveness, our findings confirm the narrow version of the Porter hypothesis that well-designed regulations provide firms incentives to innovate and will have less adverse impact on productivity than prescriptive regulations.

7. Conclusion

In this paper, by exploiting plausibly exogenous variation in the mandate on carbon intensity reduction across China's provinces, we assess the impacts of China's carbon emissions control on firm's competitiveness. We match publicly listed firms with their subsidiaries covering the period 2003–2015, to precisely measure the degree the firms exposed to the policy shock of mitigation mandate. We find consistent and robust evidence that supports the directed technical change induced by the mandates on low-carbon innovation and insignificant crowding-out effect of mitigation mandate on other types of innovation. Our results also show that firm's TFP is not affected by either the mandate directly or the induced low-carbon innovation indirectly. Therefore, we confirm the narrow version of Porter hypothesis that the target-based regulation stimulates the low-carbon innovation but does not affect firm performance measured by productivity.

In light of the recently announced carbon neutrality target in China, these results suggest that environmental mandates do not necessarily harm firm's competitiveness and they are effective at reducing greenhouse gases as evidenced by the declined energy intensity per firm. However, we find that low-carbon innovation induced by the mandate is of low quality, and serves mainly for technologies related to input augmenting. This is largely due to the fact that the mandate is intensity based target and thus does not encourage deep innovation for significantly changing the production technology related to energy. Thus, future policy design shall pay special attention to the unintended

Table 8
Effects of low-carbon innovation on firm's productivity.

	TFP (1)	*TFP* (2)	*Larbor_prodcutivity* (3)	*Larbor_prodcutivity* (4)	*Capital_productivity* (5)	*Capital_productivity* (6)
Panel A						
Exposure	−0.003	−0.003	−0.004	−0.004	−0.025***	−0.025***
	(0.003)	(0.003)	(0.007)	(0.007)	(0.009)	(0.009)
LowcarbonPat_flow	0.006		0.004		−0.010	
(lagged)	(0.006)		(0.015)		(0.020)	
LowcarbonPat_stock		0.002		−0.018		−0.015
(lagged)		(0.008)		(0.023)		(0.023)
Observations	9517	9517	9517	9517	9526	9526
R-squared	0.711	0.789	0.854	0.854	0.874	0.874
Panel B						
Exposure	−0.004	−0.004	−0.009	−0.008	−0.025***	−0.025***
	(0.003)	(0.004)	(0.008)	(0.008)	(0.009)	(0.010)
LowcarbonPat_flow	−0.034		−0.057		0.051	
(instrumented)	(0.088)		(0.223)		(0.199)	
LowcarbonPat_stock		−0.079		−0.155		0.112
(instrumented)		(0.080)		(0.181)		(0.202)
Kleibergen-Paap rk LM statistics	25.465	18.010	25.465	18.010	27.032	18.816
Cragg-Donald Wald F statistics	62.277	64.811	62.277	64.811	66.547	67.914
Kleibergen-Paap rk Wald F statistics	27.053	17.377	27.053	17.377	28.850	18.148
Observations	7333	7185	7333	7185	7341	7193

Notes: All results have controlled for firm attributes including firm's size, age, leverage, cash and Tobin's Q. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * significant at the 1%, 5%, and 10% level, respectively. IV for *LowcarbonPat* (instrumented): the average patent number of the peer firms in the same industry in the same region that year. Firm fixed effects, industry-year and province-year fixed effects are included in all models.

consequences on innovation.

Lastly, this paper also provides several possible directions for future research. Our results show that the mandate mainly induces innovations measured by the number of utility model patents. The classification of patent quality here is rather general. Previous studies have suggested to use the forward citations associated with patents and their citing information to measure innovation quality (Hall et al., 2005; Fang et al., 2017; Jaravel et al., 2018). It would be interesting the distributional impacts of the mandate on various levels of innovation quality. Moreover, we can further examine the firm's investment in green-energy technology and low-carbon technology when the data is available. Last but not the least, some recent studies have shown that political incentives are indeed central to China's decentralized program enforcement including environmental regulation.[16] Therefore, the role of local government is crucial for improving the compliances and enforcement in emission mitigations. All these will require additional data sources, and thus are left for future work.

Declaration of Competing Interest

None.

Appendix A. Appendix

Table A1
Carbon intensity reduction mandates.

Province	Reduction mandated target (%)
Beijing	18
Tianjin	19
Hebei	18
Shanxi	17
Inner Mongolia	16
Liaoning	18
Jilin	17
Heilongjiang	16
Shanghai	19
Jiangsu	19
Zhejiang	19
Anhui	17
Fujian	17.5
Jiangxi	17
Shandong	18
Henan	17
Hubei	17
Hunan	17

(*continued on next page*)

[16] These studies include Chen et al. (2018), Bo (2021), He et al. (2020).

Table A1 (*continued*)

Province	Reduction mandated target (%)
Guangdong	19.5
Guangxi	16
Hainan	11
Chongqing	17
Sichuan	17.5
Guizhou	16
Yunan	16.5
Tibet	10
Shaanxi	17
Guansu	16
Qinghai	10
Ningxia	16
Xinjiang	11

Source: "*Work Plan for Controlling Greenhouse Gas Emissions during the 12th Five-Year Plan*" issued by the China State Council in 2011.

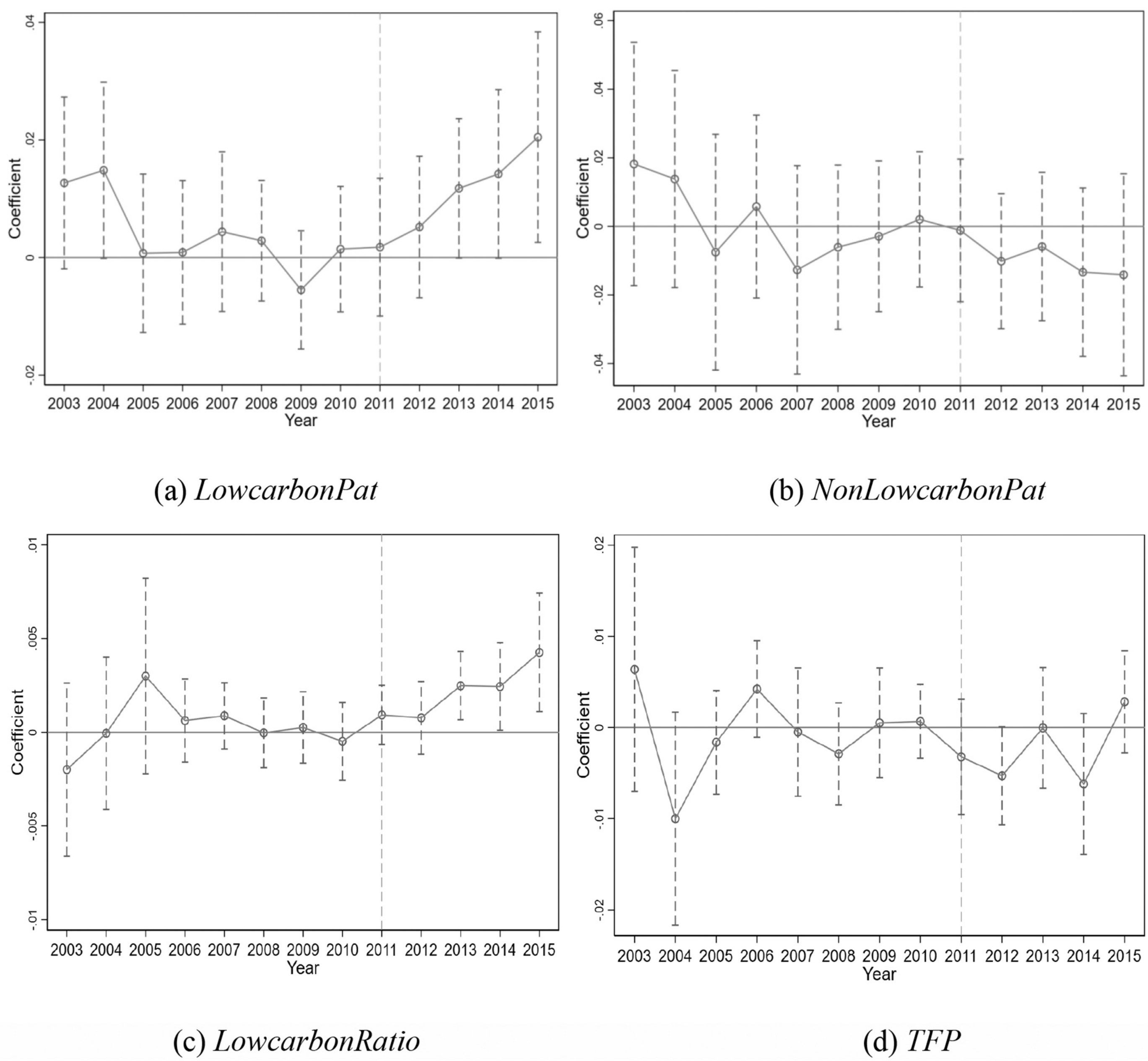

Fig. A1. Pre-trends for low-carbon innovation and TFP.
Notes: Panel (a), (b), (c) and (d) represent the pre-trend for *LowcarbonPat*, *NonLowcarbonPat*, *LowcarbonRatio* and *TFP* respectively. The vertical dashed lines represent the 95% confidence interval.

Table A2
Robustness check on firm's innovation subsidy.

Variables	*LowcarbonPat*	*NonLowcarbonPat*	*LowcarbonRatio*
	(1)	(2)	(3)
Panel A: drop firms with innovation subsidy			
Exposure	0.011**	−0.004	0.003**
	(0.006)	(0.011)	(0.001)
Adjusted R-squared	0.626	0.764	0.322
Observations	9443	9436	9436
Panel B: control for innovation subsidy (flow)			
Exposure	0.009*	−0.007	0.002***
	(0.005)	(0.009)	(0.001)
Innovation_subsidy (flow)	0.001	0.008***	$-4.04*10^{-6}$
	(0.002)	(0.002)	(0.0002)
Adjusted R-squared	0.604	0.752	0.346
Observations	12,857	12,848	12,848
Panel C: control for innovation subsidy (stock)			
Exposure	0.009*	−0.007	0.002***
	(0.005)	(0.009)	(0.001)
Innovation_subsidy (stock)	0.002	0.009***	$6.94*10^{-5}$
	(0.002)	(0.003)	(0.0002)
Adjusted R-squared	0.604	0.752	0.346
Observations	12,857	12,848	12,848
Firm attributes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes

Notes: *LowcarbonPat* refers to the low-carbon granted patent applications, *NonLowcarbonPat* represents the granted patent applications in other areas, and *LowcarbonRatio* is the ratio of low-carbon patents relative to total patents. Firm attributes include firm's size, age, leverage, cash and Tobin's Q. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * significant at the 1%, 5%, and 10% level, respectively.

Table A3
Robustness check on alternative TFP measures.

Variables	*TFP1*	*TFP2*
Exposure	−0.003	−0.003
	(0.002)	(0.002)
Firm attributes	Yes	Yes
Firm FE	Yes	Yes
Industry-year FE	Yes	Yes
Province-year FE	Yes	Yes
Observations	12,828	12,828
Adjusted R-squared	0.764	0.775

Notes: *TFP1* is measured by LP algorithm. *TFP2* is measured by Wooldridge (2009). Firm attributes include firm's size, age, leverage, cash and Tobin's Q. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * significant at the 1%, 5%, and 10% level, respectively.

Table A4
Robustness check on standard error clustering.

	LowcarbonPat	*NonLowcarbonPat*	*LowcarbonRatio*	*TFP*
	(1)	(2)	(3)	(4)
Exposure	0.009**	−0.007	0.002***	−0.002
	(0.004)	(0.009)	(0.001)	(0.003)
Firm attributes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes
Observations	12,857	12,848	12,848	12,828
Adjusted R-squared	0.604	0.752	0.347	0.685

Notes: *LowcarbonPat* refers to the low-carbon granted patent applications, *NonLowcarbonPat* represents the granted patent applications in other areas, and *LowcarbonRatio* is the ratio of low-carbon patents relative to total patents. Firm attributes include firm's size, age, leverage, cash and Tobin's Q. Robust standard errors reported in parentheses are clustered at the province-industry level. ***, **, and * significant at the 1%, 5%, and 10% level, respectively.

Table A5
Robustness check on time trend.

	LowcarbonPat		*NonLowcarbonPat*		*LowcarbonRatio*		*TFP*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure	0.009*	0.009*	−0.007	−0.007	0.002***	0.002***	−0.002	−0.002
	(0.004)	(0.005)	(0.009)	(0.009)	(0.001)	(0.001)	(0.003)	(0.002)
Trend	0.035***	0.007	0.083***	0.107***	−0.003***	−0.003*	−0.009	−0.005
	(0.008)	(0.011)	(0.018)	(0.024)	(0.001)	(0.002)	(0.006)	(0.008)
Trend_2		0.002**		−0.002		$-4.56*10^{-6}$		−0.0003
		(0.001)		(0.001)		(0.0001)		(0.0003)
Firm attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,857	12,857	12,848	12,848	12,848	12,848	12,828	12,828
Adjusted R-squared	0.605	0.605	0.752	0.753	0.347	0.347	0.685	0.685

Notes: *LowcarbonPat* refers to the low-carbon granted patent applications, *NonLowcarbonPat* represents the granted patent applications in other areas, and *LowcarbonRatio* is the ratio of low-carbon patents relative to total patents. *Trend* refers to a linear time trend, *Trend_2* refers to quadratic term of *Trend*. Firm attributes include firm's size, age, leverage, cash and Tobin's Q. Robust standard errors reported in parentheses are clustered at the province-industry level. ***, **, and * significant at the 1%, 5%, and 10% level, respectively.

Table A6
Robustness check on trade and R&D.

	LowcarbonPat	*NonLowcarbonPat*	*LowcarbonRatio*	*TFP*
	(1)	(2)	(3)	(4)
Exposure	0.009*	−0.003	0.002***	−0.0005
	(0.005)	(0.008)	(0.001)	(0.003)
Trade	0.0005	0.005	0.00004	0.0004
	(0.001)	(0.003)	(0.0002)	(0.0007)
R&D	0.0005	0.0006	−0.0001	0.00001
	(0.0009)	(0.002)	(0.0002)	(0.0004)
Firm attributes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes
Observations	10,988	10,988	10,988	10,988
Adjusted R-squared	0.638	0.764	0.408	0.700

Notes: *LowcarbonPat* refers to the low-carbon granted patent applications, *NonLowcarbonPat* represents the granted patent applications in other areas, and *LowcarbonRatio* is the ratio of low-carbon patents relative to total patents. *Trade* is the logarithm of value of firm's export and import. *R&D* refers to the logarithm of firm-level R&D investment (starting from 2007). Firm attributes include firm's size, age, leverage, cash and Tobin's Q. Robust standard errors reported in parentheses are clustered at the province-industry level. ***, **, and * significant at the 1%, 5%, and 10% level, respectively.

Table A7
Robustness check on non-random carbon reduction mandates.

	LowcarbonPat	*NonLowcarbonPat*	*LowcarbonRatio*	*TFP*
	(1)	(2)	(3)	(4)
Exposure	0.009*	−0.002	0.002***	−0.0004
	(0.005)	(0.008)	(0.001)	(0.003)
$Z_c \times f(t)$	Yes	Yes	Yes	Yes
Firm attributes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes	Yes
Observations	10,959	10,959	10,959	10,959
Adjusted R-squared	0.641	0.765	0.410	0.699

Notes: *LowcarbonPat* refers to the low-carbon granted patent applications, *NonLowcarbonPat* represents the granted patent applications in other areas, and *LowcarbonRatio* is the ratio of low-carbon patents relative to total patents. $Z_c \times f(t)$ includes interactions between six key factors used to determine provincial carbon mandates and a third-order polynomial function of time. The six key factors include *Energy Consumption*, *Carbon Emissions*, *GDP*, *Industrial Structure*, *Population* and *Forest Area*. Firm attributes include firm's size, age, leverage, cash and Tobin's Q. Robust standard errors reported in parentheses are clustered at the province-industry level. ***, **, and * significant at the 1%, 5%, and 10% level, respectively.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.105971.

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