The potential influence of the carbon market on clean technology innovation in China

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\textbf{ABSTRACT}

This paper estimates the potential influence of China’s future nationwide carbon market on clean technology innovation. To overcome data limitation issues, the energy price is adopted as a proxy for the carbon price to estimate its impact on clean innovation and R&D. Then, a counter-factual method is introduced in which the potential carbon price is mapped onto the equivalent percentage change of energy price by sector. According to our results, the carbon market shows both a redirection and a crowding-out effect on technology innovation, with the former overwhelming the latter. If the future nationwide carbon market yields a carbon price of 50 Yuan, our findings estimate that it would result in an increase in the quantity and proportion of clean invention patents in ETS-covered sectors of 2.2\% and 3\%, respectively, and in an increase in the quantity and proportion of clean utility patents of 3.6\% and 1.4\% respectively. However, the effect on overall R&D is negative, indicating that carbon costs might crowd out some R&D expenditures, but in a limited manner. Generally, the carbon market in China is expected to help redirect technology innovation onto a cleaner path.

\textbf{Key policy insights}

- China’s future ETS would help redirect technology innovation onto a cleaner path.
- Maintaining a reasonable carbon price is critical to promote clean innovation.
- A tightened cap on the ETS system would help to maintain such a reasonable carbon price.

\textbf{1. Introduction}

In 2017, China is expected to launch a nationwide carbon Emissions Trading System (ETS). In addition to its effectiveness regarding emissions abatement and its impact on economic growth, the potential influence of this market-oriented environmental policy on China’s clean technology innovation is worth studying.

In the long term, clean innovation is the key for China to achieve its emissions reduction targets and to reconcile the relationship between emissions abatement and economic growth. Nevertheless, recent ‘green’ productivity evaluations show that China is not on the path to sustainable low-carbon growth (Chen, 2015; Chen & Golley, 2014). Theoretically, despite its importance, clean technology is unlikely to achieve a socially optimal level in the absence of policy intervention. This is due to the ‘dual externality’ problem (Hall & Helmers, 2013; Jaffe, Newell, & Stavins, 2005; Ley, Stucki, & Woerter, 2016), which states that both financial market support and private sector incentives for clean innovation activities are insufficient because of the high risk and low private rewards of participation. From this perspective, climate/environmental policy is...
necessary to induce clean technology innovation, as it can increase the expected private benefits of clean technology (Bergek, Berggren, & KITE Research Group, 2014; Dechezleprêtre, Martin, & Bassi, 2016; Groba & Breitschopf, 2013). Some studies also show that China’s existing environmental policies have a positive impact on clean innovation and technology improvement (Fujii, Managi, & Kaneko, 2013; Liu & Wang, 2017; Wong, 2013).

One related theory is the Induced Technical Change (ITC) theory, which was first proposed by Hicks (1932). The ITC implies that the direction of technological change is determined by changes in the relative factor price; i.e. a higher energy price may induce energy-saving innovation. The ITC effect has been tested by a considerable body of empirical research, particularly with the use of patent data. For example, Aghion, Dechezleprêtre, Hémous, Martin, and Reenen (2016) find evidence in the automobile industry, Ley et al. (2016) study the effect in OECD industrial sectors and Popp (2002) produces empirical results using U.S. data. Moreover, energy-saving patents are found to respond quite rapidly to changes in energy prices (Brunnermeier & Cohen, 2003; Dechezleprêtre, Glachant, Haščič, Johnstone, & Ménière, 2011; Popp, 2002, 2005). Furthermore, climate/environmental policy explicitly or implicitly forms a (shadow) emissions price, which indicates that its impact on the direction of innovation might also be explained within the ITC framework (Newell, Jaffe, & Stavins, 1999).

Another strand of literature related to this paper empirically tests the Porter hypothesis. According to Porter and Van Der Linde (1995), environmental regulation may not harm firms but might instead promote innovation and even improve competitiveness. The Porter hypothesis does not provide empirical economists with a clear theoretical definition (Jaffe & Palmer, 1997). Studies test the influence of regulation on either clean innovation (the ‘weak’ version, similar to the ITC effect discussed above) or total factor productivity (TFP) and research and development (R&D) expenditures (the ‘strong’ version; Greenstone, List, & Syverson, 2012; Harrison, Hyman, Martin, & Nataraj, 2015; Jaffe & Palmer, 1997). However, the current results are typically ambiguous, particularly for the strong version of the Porter hypothesis.

Regarding evidence from carbon markets, several studies focus on the world’s largest ETS, the European Union Emissions Trading Scheme (EU ETS). Many studies believe that the EU ETS effectively incentivizes firms to engage in clean innovation activities (Borghesi, Cainelli, & Mazzanti, 2015; Martin, Muûls, & Wagner, 2013; Rogge & Hoffmann, 2010; Schmidt, Schneider, Rogge, Schuetz, & Hoffmann, 2012), at least in the short term (Hoffmann, 2007). However, some analysis shows that the impact of the system on clean innovation is weak because of institutional design problems, such as a lack of stringency, prohibition of allowances, and banking and borrowing (Rogge, Schneider, & Hoffmann, 2011; Schleich & Betz, 2005). Evidence from other ETS, such as the SO2 and NOx cap-and-trade experiences, even show a negative influence of regulation on innovation (Taylor, 2012).

What is the potential influence of China’s nationwide ETS on clean technology innovation? This paper investigates the issue by testing both the ITC (clean innovation) and the Porter (overall R&D) hypotheses in China’s industrial sectors. The contribution of this paper is threefold.

First, this paper distinguishes between the redirection effect and the crowding-out effect of the carbon price in ETS on China’s technology innovation. On the one hand, an increasing carbon price would redirect innovation onto a cleaner path. On the other hand, an increasing carbon price might also cause high costs, crowd out the overall R&D and lead to a decreasing incremental influence of the redirection effect. This is different from the linear impact of carbon pricing on innovation implied by the above-mentioned empirical studies of Aghion et al. (2016) and Ley et al. (2016).

Second, this paper employs China’s clean patents data to index clean innovation activities and to test the influence of ETS on these activities. Although the research on China’s patents data is booming (He, Li, & Fang, 2016; Wei, Xie, & Zhang, 2017), few studies examine these data in the clean innovation field in China. Patent data are demonstrated to be suitable for clean/environmentally friendly innovation studies, as these data can be classified into detailed technological fields and have been successfully applied in empirical research that uses U.S. and EU data (Dechezleprêtre et al., 2011).¹

Third, this paper proposes a method to evaluate the potential influence of an ETS under the condition of insufficient price data. Before implementing the ETS nationwide, China ran pilot markets in five cities and two provinces, beginning in 2013. However, these pilot projects have not produced sufficiently large long-term carbon price data series for empirical research, and they are not purely exogenous for quasi-experimental studies. To overcome the data limitation problem, this study designed a three-step method combining
econometric regressions and a counter-factual method referred to as 'mapping carbon price' (Cullen & Mansur, 2014). As long as the majority of industrial emissions derive from fossil fuel consumption, the carbon price is equivalent to energy costs for firms and can be treated as a markup of energy price. Additionally, the energy price is a good proxy for carbon pricing in the existing literature (Aghion et al., 2016; Ley et al., 2016; Newell et al., 1999; Popp, 2002), as variations or changes in the energy price often reflect the components of an energy-related carbon tax. Therefore, this paper uses historic energy price data to study the influence of exogenous price changes on clean innovation and R&D in regressions. Then, the carbon price’s potential range is mapped onto the equivalent percentage change in energy price by sector. The potential influence of the carbon price on clean innovation and R&D is calculated according to the mapping and the regression coefficients. These thoughts have already been applied by some studies in sporadic scenario simulations (Li & Lin, 2016; Yang, Fan, Yang, & Hu, 2014). This paper develops a method to map much wider carbon price ranges and distinguish the incremental and accumulated effects in mapping.

The remainder of this paper is structured as follows. Section 2 describes the methodology, including the empirical strategy and the carbon price mapping method applied in China’s industrial sectors. In Section 3, a panel dataset of China’s 29 industrial sectors from 2000 to 2012 is constructed. Section 4 provides empirical results and a discussion. Section 5 concludes.

2. Methodology
To overcome the data limitations in China’s nationwide carbon market, this paper designs and employs a three-step method combining econometric regressions and a counter-factual study. In the first step, static and dynamic panel data (DPD) models are constructed to estimate the influence of energy price changes on clean innovation and R&D. In the second step, one additional unit of the carbon price in China’s nationwide market is mapped onto an equivalent percentage change in the sectoral energy price. In the third step, the potential influence of carbon price on technology innovation, in terms of both incremental effects and accumulated effects, is calculated with the regression coefficients and the mapping relationship.

2.1. Econometric models and estimation strategy
2.1.1. The price-induced clean innovation model
The first model finds the relationship between the percentage change in industrial clean patents (or its proportion) in response to the change in energy price, which tests the theory of energy price-induced clean innovation. As suggested by Ley et al. (2016), a log–log linear form model is applied here to estimate the elasticity coefficients. The static panel data model is as follows:

\[
\ln \text{patent}_{it} = \alpha_0 + \alpha_1 \ln \text{pe}_{it} + \mathbf{X}_{it} \mathbf{a} + \mu_t + \eta_i + \varepsilon_{it},
\]

where \(i\) and \(t\) are sector and time, respectively; \(\text{patent}_{it}\) is the quantity or proportion of clean patents (the former is used to capture the total change in clean innovation, while the latter measures the change in clean patents relative to the total scale); \(\text{pe}_{it}\) is the sectoral energy price index; and \(\mathbf{X}_{it}\) is the control variable matrix. In addition, \(\mu_t\) and \(\eta_i\) represent non-observable effects that are fixed with sector and time, and \(\varepsilon_{it}\) is a random error term.

However, the static model neither takes path dependency into account nor stresses the endogeneity issue. First, the direction of innovation may depend on its historic path (Aghion et al., 2016; Ruttan, 1997). Second, in equilibrium, the direction of innovation (which reflects the relative marginal products of inputs) and factor prices are simultaneously determined, which is one source of endogeneity bias. Therefore, a DPD model is introduced here based on the static model, in which a lagged term of log patents is added into the regressions to reveal the accumulated impact of the previous clean innovation on the current period. By taking the first difference and introducing instrument variables (IVs), the General Moment Method (GMM) estimator of the DPD model can partly solve the endogeneity problem. The DPD model can be written as follows:

\[
\ln \text{patent}_{it} = \gamma_0 + \gamma_1 \ln \text{patent}_{it-1} + \gamma_2 \ln \text{pe}_{it} + \mathbf{X}_{it} \mathbf{r} + \mu_t + \eta_i + \varepsilon_{it}.
\]
2.1.2. The Porter hypothesis model
The second model estimates the percentage change in overall R&D expenditure in response to the change in energy price, which is a test of the Porter hypothesis, as suggested by Jaffe and Palmer (1997). The model is similar to the ITC model, except that the dependent variable here is the sectoral per capita R&D stock:

\[
\ln r_d = \beta_0 + \beta_1 \ln p_e + X_i \beta + \varphi_i + \theta_i + \epsilon_i. \tag{3}
\]

Similarly, a DPD model is also introduced according to Equation (3) in consideration of the path dependency and endogeneity problem:

\[
\ln r_d = \delta_0 + \delta_1 \ln r_{d-1} + \delta_2 \ln p_e + X_i q + \varphi_i + \theta_i + \epsilon_i \tag{4}
\]

2.1.3. Estimation
The static fixed effect models are estimated with the ‘areg’ command in Stata 13. The command corrects the degree of freedom in estimation, as suggested by Acemoglu and Johnson (2007).

The GMM estimation is applied in the DPD model to solve the endogeneity problem. There are two types of GMM estimations for DPD models. The first is the first-differenced GMM, which can eliminate time-invariant unobservable effects and thus partially solve omitted variable bias and weaken reverse causation bias. The second, the system GMM method, can reduce bias in the estimated coefficients and improve efficiency by simultaneously estimating a system of both the first-differenced and level equations (Blundell & Bond, 1998). This paper adopts the latter estimation.

2.2. Mapping carbon pricing
The carbon pricing mapping method finds the equivalent percentage change in unit energy cost (energy price) for each incremental carbon price unit, which is named the incremental cost of carbon (IC).2 As most industrial carbon costs come from energy consumption, carbon price can be treated as an addition to energy cost (price). This relationship varies by sector because the energy mix in each sector is different. The mapping method follows two steps. The first is to calculate the equivalent energy cost of one carbon price unit, named the unit cost of carbon (UCarbon), which is sectoral total cost of one carbon price unit divided by the sectoral total energy consumption:

\[
UCarbon = \frac{1 \sum e_f \cdot E_s}{E}, \tag{5}
\]

where UCarbon is the unit cost of one carbon price unit (Yuan/tce),\(^4\) \(e_f\) is the emissions coefficient by fuel type, where subscript \(s\) denotes coal, gasoline, diesel, natural gas and electricity; \(E_s\) is the consumption by fuel type; \(E\) is the total energy consumption in standard coal equivalent (tce) by sector and 1 is the carbon price unit (which here in China is Yuan/ton CO\(_2\)).

The second step is to calculate the incremental cost of one additional carbon price unit on the percentage change in the sectoral unit energy cost:

\[
IC_j = \frac{UCarbon}{pe + (j - 1) \cdot UCarbon} \times 100\%, \tag{6}
\]

where \(j\) is the carbon price level, and \(pe = \sum P_s \cdot E_s / E\), representing the sectoral energy cost per energy consumption (Yuan/tce). The denominator of Equation (6) shows the total energy cost at carbon price level \(j\), including the preceding units of carbon prices that have already been mapped. Therefore, \(IC\) is decreasing with \(j\), though the total cost of carbon price is larger.

2.3. Illustrating the counter-factual effect of the carbon market
The estimated coefficient of the logarithm of energy price from Section 2.1 is an elasticity that reflects the percentage change in China’s industrial clean patents or R&D in response to a one-percentage change in energy...
price. Section 2.2 provides counter-factual scenarios, mapping the incremental cost of carbon prices onto the percentage change in energy price. Therefore, the product of the estimated coefficient and the mapping relationship in Equation (6) is a semi-elasticity that shows the potential incremental effect \( IE \), which is the percentage change in China’s industrial clean innovation or R&D activities in response to one additional carbon price unit:

\[
IE_j = \text{coef}_1 \cdot IC_j,
\]

where \( IE_j \) is the incremental effect of the \( j \)th carbon price unit on the percentage change in clean innovation or R&D; \( \text{coef}_1 \) is the estimated coefficient, which is either \( \gamma_2 \) or \( \delta_2 \).

The potential effect of a carbon price at the \( j \) level, which is our interest, is therefore captured by the accumulated effect \( ACE_j \) of all of the incremental effects:

\[
ACE_j = (1 + ACE_{j-1}) \cdot (1 + IE_j) - 1.
\]

### 3. Data

#### 3.1. Clean patents in China

This paper establishes a clean patent dataset in China’s industrial sectors from 2000 to 2012. The year 2000 is taken as the first year, as it marks the launch of China’s new Intellectual Property Protection Law.

Clean patents are searched for in the database of the State Intellectual Property Office of China using the Clean Patent Inventory listed International Patent Classification (IPC) code provided by World Intellectual Property Organization. Inventions and utilities, which are two types of Chinese patents with descending innovation content,\(^5\) are searched separately. Then, the clean patents are classified into International Standard Industrial Classification (ISIC) sectors. The relationship between the IPC and ISIC is not typically one-to-one. OECD Concor-dance is used to conduct the matching process. The sector-of-use rule is selected instead of the industry-of-manufacturing, as the former is more economically meaningful (details in Appendix 1). ISIC-classified clean patents are finally transferred into 29 2-digit China Industry Classifications (Appendix Table A1).

#### 3.2. R&D

R&D per capita, which is the ratio between R&D stock and sectoral employees, is used as the indicator of R&D. The calculation of R&D stock follows the Perpetual Inventory Method and the sectoral R&D flow data from the *China Statistical Yearbook of Science and Technology*.

#### 3.3. Sectoral energy price index

China has not published official synthesis energy price data. The sectoral energy price index is calculated from the prices of coal, gasoline, diesel, natural gas and electricity, weighted by their consumption (Ley et al., 2016).

\[
pe_{it} = \sum_s P_{s, it} \cdot E_{s, it} / E_{it}
\]

where \( P_{s, it} \) and \( E_{s, it} \) are fuel and electricity prices and their consumption; \( E_{it} \) is the total energy consumption. \( P_{s, it} \) is obtained from the *Price Yearbook of China*, where the National Statistics Bureau published the prices by fuel type in 36 large and medium-sized cities from 2002 to 2005. The average price of each fuel is extended with the Producer Price Index (PPI) in the corresponding energy sector (Li & Lin, 2016; Ma, Oxley, & Gibson, 2009; Ma, Oxley, Gibson, & Kim, 2008).

#### 3.4. Carbon price

China has not launched its nationwide carbon market. This paper uses a wide range of carbon price scenarios, from 1 to 500 Yuan RMB, in the counter-factual mapping procedure and presents the results. In particular, this
paper reports selected results of a 50 Yuan and a 100 Yuan carbon price; the former refers to the pilots’ average prices (Table 1), and the latter is a high but still reasonable expectation for the nationwide market. All simulation results of carbon prices up to 500 Yuan (approximately 75 USD) are reported in graphs to take into account wider possibilities.

3.5. Control variable data

Control variables in econometric models (Equations (1)–(4)) include indicators of the following aspects.

First, the production of knowledge is included as a control variable. One indicator is capital deepening (K/L), defined as the ratio of capital stock and labour in sectors, following Chen (2011) and Wang and Qi (2014). Additionally, in Equations (1) and (2), where the dependent variable is patents, the models also include R&D per capita because R&D is often treated as the input of patent production.

Second, the sectoral energy mix is included, as it can exert different pressures via the sectoral energy cost on clean innovation. The proportion of coal consumption is used as the indicator.

Third, the institutional features of sectors are included. One indicator is the proportion of state-owned assets. On average, state-owned enterprises are less innovative (He et al., 2016; Wei et al., 2017), but in terms of price-induced clean innovation, the opposite might be true since they typically face stronger environmental policy regulations. Another indicator is industrial concentration, which is measured by the proportion of large and medium-sized firms and reflects the influence of competition on innovation. The square term of it is also introduced to capture the possible inverted-U relationships as a combination of the ‘escape-competition effect’ and the ‘Schumpeterian effect’ (Aghion, Bloom, Blundell, Grigth, & Howitt, 2005; Hashmi, 2013). The former reflects the increasing innovation willingness among leading firms to pursue profit under intense competition, while the latter shows the opposite incentives for laggards.

All the above data come from China Statistical Yearbook, China Energy Statistical Yearbook and China Labour Statistical Yearbook.

Simultaneous increasing trends are found in clean patents, R&D and energy price index line plots, as the empirical assumption expected (Figure 1). In 2008, the energy price index decreases slightly, but it immediately returns to the increasing path in 2009.

The descriptive statistics of the key variables are presented in Table 2. Additionally, panel data unit root tests, including the LLC, IPS, ADF-Fisher and Hadri tests, find stationary values at the level value for all indicators (detailed tests results are reported in Appendix Table A2).

4. Results and discussion

4.1. Results of empirical models

The empirical results of the ITC model and the Porter hypothesis model are reported in Tables 3 and 4, respectively. In Table 3, the price-induced innovation effect is tested for both clean inventions and clean utilities, and within each class of patent, the quantity and proportion of clean patents are also tested separately. For each dependent variable, the results of a static model and a DPD model with a system GMM estimator are provided for comparison. In the static models, the $R^2$ values are higher than 0.9. In all dynamic models, the Hansen test results show the validity of the instruments, and the AR test results cannot reject the ‘no autocorrelation of order 2’ null hypothesis, which is required by the GMM estimation.

The energy price, as a proxy for the carbon price, has a significant and positive effect on both the quantity and proportion of clean patents, and the only exception is when the dependent variable is the proportion of clean patents.
The results reveal two features. First, comparing the static and dynamic model results reveals an overestimation of the inducement effect of the energy price in the static model. Second, the energy price could increase both the quantity and proportion of clean patents, which implies a redirection effect of energy price; this would help lead the innovation onto a cleaner path.

The results of other variables are as follows. First, the lagged terms of the dependent variables in the dynamic models are all significantly positive, which coincides with the path-dependency effect of innovation in other relevant studies (Aghion et al., 2016). Second, for the ‘input’ of innovation, per capita R&D shows a positive effect on clean innovation, especially for utility patents; by contrast, the effect of capital deepening in most models is negative, indicating that the existing capital investment is not directed at clean innovation. The only exception in model (5) might be caused by endogeneity problems in the static model. Third, the influence of the sectoral coal proportion is not significant in most models. It might be that most of the effect of fuel mix is captured by the synthesized energy price in our dataset. Fourth, for the institutional features, sectors with a higher proportion of state-owned assets tend to perform better with respect to clean innovation. The coefficients of industrial concentration indicate that competition may spur more clean innovation, and the effect could be non-linear in some cases.

Table 4 reports the results of the Porter hypothesis test, where the dependent variable is logarithm R&D per capita. The Porter hypothesis results for China’s industrial sectors are ambiguously negative. In the first static models, the coefficient of \( \ln(pe) \) is positive at the 1% significance level. When the lagged term of dependent variable is controlled in model (2), the coefficient becomes negative but insignificant. When the DPD models (model 3) are introduced, the coefficient is negative at the 5% significance level. The reason underlying these results may be twofold. First, most of the influence on R&D is explained by the lagged term of the dependent variables in the dynamic model. Second, the system GMM estimator can better correct the endogeneity bias.

Therefore, the coefficients of model (3) are used for explanatory purposes. An exogenous increase in the energy price may lead to a slight decrease in sectoral R&D per capita, which may reflect a crowding-out effect of energy cost on overall R&D expenditures.

4.2. Results of mapping the carbon price

4.2.1. The sectoral heterogeneity mapping relationship between carbon price and energy price

According to Equations (5) and (6), the equivalent percentage change in energy price caused by the one carbon price unit (1 Yuan) will be heterogeneous among sectors. This cost of the first carbon price unit is 0.07% on
average and ranges from 0.02% to 0.24%. Moreover, the incremental cost of one additional carbon price unit is decreasing: at the given carbon prices of 50, 100 and 500 Yuan, they are 0.068%, 0.065% and 0.048% respectively.

Of the 29 sectors in this paper, 7 will be covered by the future nationwide ETS; these sectors are petroleum processing (14), power and heat (28), non-metal products (19), paper products (12), ferrous metals (20), chemicals (15), non-ferrous metals (21) and transport equipment (24). Specifically, the equivalent energy price changes caused by one additional carbon price unit in the ETS sectors (0.111% at 50 Yuan and 0.104% at 100 Yuan on average) are considerably larger than they would be in the non-ETS sectors (0.052% at 50 Yuan and 0.050% at 100 Yuan). For more scenarios, the incremental costs of carbon prices from 1 to 50 Yuan are plotted in Appendix Figure A2.
The potential effect of nationwide ETS on clean innovation is ascending as carbon price increases (Figure 2), according to Equation (8). Nevertheless, the curves bend slightly downward as the incremental effect of one additional carbon price unit descends, as implied by Section 4.2.1 and illustrated in Figure 3. The above results show a redirection effect of carbon price on innovation. With regard to the quantity of clean patents, given the carbon price, the influence on clean utilities is greater than that on clean inventions, whereas for the proportion of clean patents, the influence on clean inventions is greater. This result implies that the carbon price may cause overall utility patents (which typically embody less innovative activity) to increase more rapidly than clean utility patents but to result in a faster growth rate of clean inventions than overall invention patents (which typically embody high-quality innovation). Thus, the carbon price could redirect innovation activities to cleaner technologies, particularly for high-quality innovations.

The declining incremental influence also reflects part of the crowding-out effect of the carbon price. As the carbon price increases, its marginal positive contribution to clean innovation becomes smaller. This result implies that the carbon price may cause overall utility patents (which typically embody less innovative activity) to increase more rapidly than clean utility patents but to result in a faster growth rate of clean inventions than overall invention patents (which typically embody high-quality innovation). Thus, the carbon price could redirect innovation activities to cleaner technologies, particularly for high-quality innovations.

The declining incremental influence also reflects part of the crowding-out effect of the carbon price. As the carbon price increases, its marginal positive contribution to clean innovation becomes smaller. The possible reason is that increasing carbon costs may crowd out part of the innovation resources.

Within ETS coverage, in the petroleum processing sector (14), a carbon price of 50 Yuan could accumulatively induce 4.32% and 5.86% increases in the quantity and proportion of clean inventions and 7.01% and 2.66% increases in the quantity and proportion of clean utilities, respectively. In the power and heat sector (28), it could induce 2.71% and 3.68% increases in the quantity and proportion of clean inventions and 4.39% and 1.67% increases in the quantity and proportion of clean utilities. The smallest influence is found in the transport equipment (24), in which the given carbon price would induce 0.66% and 0.88% increases in the quantity and proportion of clean inventions and 1.05% and 0.41% increases in the quantity and proportion of clean utilities. At a carbon price of 100 Yuan, the accumulated effect is less than doubled. Scenarios of accumulated effects with the carbon price ranging from 1 to 500 Yuan are shown in Figure 2.
4.2.3. The effects of the carbon price on R&D

The influence of the carbon price on sectoral overall R&D expenditure is negative. Given a carbon price of 50 Yuan, industrial R&D expenditure would decrease by 0.49%, while for ETS sectors, the average effect is 0.81%, which is also very limited. The result here cannot support the strong version of the Porter hypotheses, which states that environmental regulation may even enhance overall R&D abilities. In contrast, this result is further evidence of the crowding-effect whereby the carbon costs may crowd out the research inputs. Nevertheless, the effect is limited.

4.3. Discussion

One problem of the ‘mapping carbon pricing’ methodology is that it can reflect only a potential effect of the carbon price. The carbon costs may not fully pass through to generate motivation for clean innovation and research activities. Therefore, the effects suggested by this method are the upper limit of induced innovation and the Porter effect of China’s carbon markets. Nevertheless, until China’s carbon market launches, no long-term, continuous carbon price data are available at the national level. This methodology can provide a counter-factual estimation of the influence of carbon prices.

The second problem relates to the competitiveness issue. If the carbon price were largely passed through to the final product price, it would injure the sectoral competitiveness and thus might affect its innovation ability. To test whether this negative impact might occur, a two-step regression has been used in the robustness test. In the first step, the log PPI has been regressed on the log energy price, capital price and labour price and divided into an ‘energy price component’ and an ‘other factors component’, according to the estimation. In the second step, the two components are included in the independent variables of the regressions in Sections 2.1.1 and 2.1.2 to substitute for the log energy price. The results show that the coefficients of the first component,
which reflects both the direct effect of energy price on clean patents/R&D and the indirect effect through PPI, are still positive in the clean patents regressions (Appendix Table A3) and negative in the R&D regressions (Appendix Table A4), controlling for other factors that might affect the competitiveness, which has been captured by the second component. This implies that the redirection effect is still positive, and the crowding-out effect also exists even if the competitiveness issue is taken account.

Another potential problem is that this paper uses only industrial data. The supply of clean innovation activities may not be limited to industrial sectors because the carbon market will increase the demand for clean innovation. This paper avoids this problem as much as possible by counting patents with applicants who are not only industrial firms but also other institutions and individuals. In addition, clean patents have been matched into the sectoral classification based on the Sector of Using rule (Johnson, 2002; see more details in Appendix 1). Thus, to some extent, the indicators reflect the demand for clean innovation.

The last issue is to test whether a non-linear relationship exists between energy price and clean innovation. The square terms have been added into the regressions, but their coefficients are insignificant and not robust. This indicates a lack of a significant non-linear relationship, for example, the inverse-U-shaped impact of the energy price onto clean innovation and R&D.

5. Implications and conclusion

This paper estimates the potential influence of China’s carbon market on clean technology innovation. By imposing a carbon price on covered firms, a carbon market would generate both a redirection effect and a crowding-out effect on technology innovation according to our results.

An increasing carbon price would help redirect high-quality innovation activities to induce clean technology innovation. In particular, if the nationwide ETS yielded a carbon price of 50 Yuan, our findings suggest that the
quantity and proportion of clean invention patents in the covered sectors would increase by an average of 2.2% and 3%, respectively, and the quantity and proportion of clean utility patents would increase by an average of 3.6% and 1.4%, respectively. At a carbon price of 100 Yuan, the effect would be less than doubled. In addition, the influence on the ETS-covered sectors would be generally larger than it would be on the non-ETS sectors, among which the petroleum processing sector and the power and heat sector would be most affected and the transport equipment sector would be least affected.

However, a higher carbon price generates diminishing marginal return in terms of clean innovation, and an excessively high carbon price may also crowd out R&D resources, showing a crowding-out effect. Specifically, the incremental effect of an additional carbon price unit diminishes due to increasing carbon costs. And the accumulated effect on overall R&D is even negative, indicating that carbon costs might crowd out R&D expenditure. Nevertheless, this effect would be limited even with extremely high carbon price scenarios.

Therefore, in implementation, it is necessary to design mechanisms within the ETS that maintain a reasonable carbon price. From the supply side, a tightened allowance cap is the most crucial mechanism. Moreover, flexible mechanisms of cap and allowances, such as banking/borrowing, allowances and reserve/cancellation provisions, are also proposed to enhance the flexibility of the supply curve and cope with shocks and uncertainties. Additionally, price stabilization mechanisms such as price floors might also be necessary to avoid extreme price fluctuation. From the demand side, the transaction is suggested to be open to diverse investors. Additionally, strictly implementing the compliance and MRV rules are also helpful for the market to transmit carbon price signals.

Notes
1. Nevertheless, due to data limits, many current studies using China’s data still use the clean TFP index, such as Xie, Yuan, and Huang (2017) (doi.org/10.1016/j.ecolecon.2016.10.019) and Wang and Shen (2016) (doi.org/10.1016/j.jser.2016.05.048). One can also find several related studies in Chinese, such as Tu and Chen (2015) (http://www.cnki.com.cn/Article/CJFDTotal-JYYJ201507013.htm) and Jing and Zhang (2014) (http://www.cnki.com.cn/Article/CJFDTotal-JYYJ201409003.htm).
2. Here, the carbon price increases 1 unit by 1 unit to j level, and the incremental cost reflects the outcome of an additional 1 unit increase in carbon price.
3. Equation (5) comes from the following relationship: equivalent unit energy cost of carbon ($UC_{\text{carbon}}$) * energy consumption ($E$) = unit carbon price (1) * sectoral carbon emissions ($\sum e_f \cdot E_s$).
4. The sectoral subscript is omitted in the equation.
5. In China, invention patents provide a 20-year-long protection period but also require a longer application procedure; utility patents provide a 10-year-long protection period but are easier to apply for.

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Appendices

Appendix 1. Matching China’s clean patents into industrial sectors

China’s clean patents are searched for in the Patent Database of the State Intellectual Property Office of China (SIPO). The clean patent categories are identified based on the International Patent Classification (IPC) code in the ‘Green Patents Inventory’ of the World Intellectual Property Organization (WIPO). Invention and utility patents that were applied for during 2000–2012 have been searched by using the application date. Applicants are not limited to firms. Other institutions and individuals have also been included because the carbon market may not only increase the innovation activities of the affected firms but also increase demand for clean technology in the technology markets, in turn stimulating related innovation by other entities.

Clean patents are aggregated into the CIC 2-digit sectoral level. One problem in this regard is that the IPC are classified based on technology types, and there is a multi-to-multi relationship between IPC code and industrial classifications. This paper uses the OECD Concordance (Johnson, 2002) to solve this problem. The OECD Concordance aggregates patents into sector classifications based on two rules known as Industry of Manufacturing (IOM) and Sector of Using (SOU). The SOU aggregation is more meaningful in the sense that the sector that uses a clean patent is the one that demands and invests in them and is most affected by the carbon markets. For example, the power generation sector demands and invests in clean inventions the most, but manufacturing these inventions remains in the machinery sector. Figure A1 shows that under the IOM rule, the clean inventions quantity in Machinery (23) is extremely high, whereas that in the power sector is small. However, with the SOU rule, the power sector is assigned much greater numbers of clean inventions, whereas that in the machinery sector decreases. This paper does not apply the more recent APL Concordance because its result is much more like the OECD IOM rule (Lybbert and Zolas, 2014). Clean patents are first matched into the International Standard Industrial Classification (ISIC) and then transferred into the CIC sectors.
Figure A1. Comparing sectoral clean inventions data by SOU and IOM.

Appendix 2. China’s industry classification: from 36 sectors to 29 sectors

Table A1. China’s industry classification.

| Sector no. (this paper) | Sector name (this paper)                                      | China standard industrial classification                                      |
|------------------------|----------------------------------------------------------------|--------------------------------------------------------------------------------|
| 1                      | Coal mining                                                     | Coal Mining and Washing of Coal                                                |
| 2                      | Petroleum and gas                                               | Extraction of Petroleum and Natural Gas                                       |
| 3                      | Metal mining                                                    | Mining and Processing of Ferrous Metal Ores                                   |
|                        |                                                                | Mining and Processing of Non-Ferrous Metal Ores                               |
| 4                      | Nonmetal mining                                                 | Mining and Processing of Nonmetal Ores and Other Ores                        |
| 5                      | Food and beverages                                              | Processing of Food from Agricultural Products                                |
|                        |                                                                | Manufacture of Foods                                                          |
|                        |                                                                | Manufacture of Beverages                                                      |
| 6                      | Tobacco                                                         | Manufacture of Tobacco                                                        |
| 7                      | Textile                                                         | Manufacture of Textile                                                        |
| 8                      | Clothing                                                        | Manufacture of Textile Wearing Apparel, Footware, and Caps                    |
| 9                      | Leather and Fur                                                 | Manufacture of Leather, Fur, Feather and Related Products                    |
| 10                     | Wood Product                                                    | Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products |
| 11                     | Furniture                                                       | Manufacture of Furniture                                                       |
| 12                     | Paper products                                                  | Manufacture of Paper and Paper Products                                        |
| 13                     | Printing                                                        | Printing, Reproduction of Recording Media                                     |
| 14                     | Petroleum processing                                            | Processing of Petroleum, Coking, Nuclear Fuel                                |
| 15                     | Chemicals                                                       | Manufacture of Raw Chemical Materials and Chemical Products                  |
| 16                     | Medicines                                                       | Manufacture of Medicines                                                       |
| 17                     | Chemical fibers                                                 | Manufacture of Chemical Fibers                                                 |
| 18                     | Rubber and Plastics                                             | Manufacture of Rubber                                                          |

(Continued)
Appendix 3. Panel unit root tests results

Panel data unit root tests including LLC, IPS, ADF – Fisher and Hardri tests have been conducted to the key variables (Table A2). For all the variables, the results are stationary at their level value. Specifically, the first three tests reject the null hypothesis that the unit root exists; the last one cannot reject the null hypothesis that the unit root does not exist.

Table A2. Panel unit root test results.

| Variables                        | LLC     | IPS     | Fisher-ADF | Hadri   | Result     |
|----------------------------------|---------|---------|------------|---------|------------|
| ln(Clean Inventions Quantity)    | −5.1796*** (0.0000) | −4.6066*** (0.0000) | 122.3117*** (0.0000) | 6.3046*** (0.0000) | Stationary |
| ln(Clean Inventions Proportion)  | −5.1859*** (0.0000) | −4.6179*** (0.0000) | 122.1587*** (0.0000) | 6.3031*** (0.0000) | Stationary |
| ln(Clean Utilities Quantity)     | −7.0422*** (0.0000) | −3.2878*** (0.0000) | 132.7218*** (0.0000) | 5.6193*** (0.0000) | Stationary |
| ln(Clean Utilities Proportion)   | −7.0207*** (0.0000) | −3.2590*** (0.0000) | 132.8428*** (0.0000) | 5.6192*** (0.0000) | Stationary |
| ln(pe)                           | −5.5572*** (0.0000) | −2.6232** (0.0044) | 114.2458*** (0.0000) | 6.0606*** (0.0000) | Stationary |
| ln(rd)                           | −3.1139*** (0.0009) | −0.8580 (0.1954) | 127.9829*** (0.0000) | 6.9071*** (0.0000) | Stationary |
| ln(K/L)                          | −3.2846*** (0.0005) | −4.6961*** (0.0000) | 162.1688*** (0.0000) | 6.3132*** (0.0000) | Stationary |
| ln(coal)                         | −2.0296* (0.0212) | −4.0802*** (0.0000) | 134.0234*** (0.0000) | 5.8875*** (0.0000) | Stationary |
| ln(SOE)                          | −7.4459*** (0.0000) | −2.1148* (0.0172) | 151.6633*** (0.0000) | 6.8315*** (0.0000) | Stationary |
| ln(CR)                           | −5.3408*** (0.0000) | −2.9193** (0.0018) | 239.6176*** (0.0000) | 6.7665*** (0.0000) | Stationary |
Appendix 4. The incremental cost of the carbon price

Figure A2. The incremental cost the carbon price on the percentage change of energy costs in the ETS sectors.
Note: the incremental cost here refers to the percentage increase of sectoral energy costs.

Appendix 5. Robustness test results

To test whether the carbon market may injure the sectoral competitiveness, and thus affect the innovation ability, a two-step regression has been used in the robustness test. In the first step, the log PPI has been regressed on the log energy price, capital price and labor price. And an ‘energy price component’ can be obtained by multiply the log energy price with its estimated coefficient; an ‘other factors component’ equals to the dependent variable minus the first component. In the second step, the two components are included in the independent variables of the regressions in Sections 2.1.1 and 2.1.2 to substitute for the log energy price. The coefficients of the first component (ln(PPIfit)) reflect both the direct effect of energy price on clean patents/R&D and the indirect effect through PPI, controlling for other factors that might affect the competitiveness, which has been captured by the second component (ln(PPINonfit)). The results in Tables A3 and A4 show that coefficients of the first components are consistent with the coefficients of log energy prices in Tables 3 and 4.
### Table A3. The influence of PPI on clean innovation.

|                      | Clean inventions | Clean utilities |
|----------------------|-----------------|-----------------|
|                      | Quantity        | Proportion      | Quantity        | Proportion      |
|                      | FE (1)          | Sys-GMM (2)     | FE (5)          | Sys-GMM (6)     |
|                      | Sys-GMM (3)     | Sys-GMM (4)     | FE (7)          | Sys-GMM (8)     |
| Lagged Depend. Var.  | 0.9097***       | 1.0566***       | 0.8167***       | 0.8224***       |
| ln(PPIfin)           | 2.4297***       | 1.7306***       | 1.1695*         | 1.6586***       |
|                      | (0.4858)        | (0.4317)        | (0.4709)        | (0.4278)        |
| ln(PPInonfit)        | 0.0096          | 0.1802          | 0.0471          | 0.1592          |
|                      | (0.1188)        | (0.1587)        | (0.1151)        | (0.1539)        |
| ln(r)                | 0.4713***       | 0.0666          | 0.2760***       | 0.1324          |
|                      | (0.0688)        | (0.1422)        | (0.0667)        | (0.1296)        |
| ln(K/L)              | -0.1174         | -0.4472***      | -0.2550*        | -0.4410***      |
|                      | (0.1185)        | (0.1162)        | (0.1149)        | (0.1280)        |
| ln(coal)             | -0.1275         | -0.0857         | -0.0733         | -0.3380*        |
|                      | (0.1026)        | (0.1801)        | (0.0995)        | (0.1739)        |
| ln(SOE)              | 0.2177***       | 0.3657***       | 0.2491***       | 0.2900***       |
|                      | (0.0627)        | (0.0482)        | (0.0608)        | (0.0566)        |
| ln(CR)               | 0.9435***       | 0.0641          | 0.7423**        | 0.1449          |
|                      | (0.2560)        | (0.5846)        | (0.2482)        | (0.4640)        |
| ln(CR)²              | 0.2196***       | -0.0204         | 0.1754**        | -0.0689         |
|                      | (0.0601)        | (0.1501)        | (0.0583)        | (0.1182)        |
| ln(t)                | 0.6068***       | 0.1328*         | 0.1239*         | 0.0960          |
|                      | (0.0525)        | (0.0619)        | (0.0509)        | (0.0537)        |
| ln(coal)             | -2.1456*        | 1.951*          | -10.7769***     | 3.3141*         |
|                      | (0.8271)        | (0.8844)        | (0.8016)        | (1.2484)        |
| Obs                  | 364             | 336             | 364             | 336             |
| R²                   | 0.987           | 0.986           | 0.986           | 0.987           |
| Hansen’s test p      | 0.7741          | 0.7343          | 0.7600          | 0.7594          |
| AR(1) p              | 0.0001          | 0.0000          | 0.0091          | 0.0114          |
| AR(2) p              | 0.4112          | 0.4781          | 0.3467          | 0.1215          |

Note: standard errors in brackets. In the GMM estimation, the fit PPI, the nonfit PPI, the proportion of state-owned assets, industry concentration and time trends are taken as exogenous variables; the rest are endogenous variables.

* p < .1, ** p < .05, *** p < .01, 00 p < .001.

### Table A4. The influence of PPI on R&D.

|                      | ln(r)            |
|----------------------|-----------------|
|                      | LSDV (1)        | LSDV-llrd (2)  | Sys-GMM (3)    |
| Lagged Depend. Var.  | 0.9359***       | 0.9305***      |
| ln(PPIfin)           | 2.2341***       | 0.1654         | 0.3246*        |
|                      | (0.4217)        | (0.1312)       | (0.1533)       |
| ln(PPInonfit)        | 0.3732***       | 0.0462         | -0.0746**      |
|                      | (0.1048)        | (0.0296)       | (0.0269)       |
| ln(K/L)              | 0.6590***       | -0.0344        | 0.0344         |
|                      | (0.0919)        | (0.0279)       | (0.0404)       |
| ln(coal)             | -0.3145***      | -0.0518*       | 0.0025         |
|                      | (0.0847)        | (0.0241)       | (0.0367)       |
| ln(SOE)              | -0.3715***      | -0.0176        | -0.0073        |
|                      | (0.0525)        | (0.0156)       | (0.0210)       |
| ln(CR)               | 0.4466*         | -0.1273*       | -0.4140***     |
|                      | (0.2263)        | (0.0628)       | (0.0912)       |
| ln(CR)²              | 0.0491          | -0.0367*       | -0.1159***     |
|                      | (0.0537)        | (0.0148)       | (0.0241)       |
| ln(t)                | 0.2111***       | 0.1399***      | 0.1691***      |
|                      | (0.0441)        | (0.0207)       | (0.0157)       |
| Constant             | 10.8814***      | 0.7346***      | 0.4275*        |
|                      | (0.3490)        | (0.1931)       | (0.1742)       |

(Continued)
Table A4. Continued.

|                  | LSDV (1) | LSDV-llrd (2) | Sys-GMM (3) |
|------------------|----------|---------------|-------------|
| Depend. Var.     |          |               |             |
| Obs              | 377      | 348           | 348         |
| $R^2$            | 0.980    | 0.999         | 1.0000      |
| Hansen's test $p$|          |               |             |
| AR(1) $p$        |          |               | 0.0051      |
| AR(2) $p$        |          |               | 0.7425      |

Note: standard errors are in brackets. In the GMM estimation, the fit PPI, the nonfit PPI, the proportion of state-owned assets, industry concentration and time trends are taken as exogenous variables; the rest are endogenous variables.

$^*$ $p < .1$, $^*$ $p < .05$, $^{**} p < .01$, $^{***} p < .001$. 