Forest Carbon Sequestration Demand Based on Emissions Reduction in China's Thermal Power and Steel Industries: Implications for Tobacco Industry

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Objectives: China is a large country of tobacco production and consumption. In the construction and development of carbon market, the tobacco industry is expected to realizing energy conservation and emission reduction by participating in carbon trading, especially focusing on the forest carbon sequestration demand based on emissions reduction. Compared with the tobacco industry, the heavy pollution industries participate in the carbon market more deeply and widely. Therefore, this paper takes thermal power and steel industries as the research object, in order to provide some implications for the emission reduction path of tobacco industry. It considers the CO2 emissions intensity and marginal abatement costs (MAC) between China's thermal power and steel industries during 2005–2017, and quantifies the forest carbon sequestration (FCS) demand level of these two industries to account for the role and potential of the forests for China's green and low-carbon development. Methods: It uses a logistic algorithm to reflect the relationship among FCS demand, MAC and other influencing factors, and the cloud model to simulate FCS demand in different scenarios. Results: It shows an average decline of 54.06% and 56.05% in the carbon intensity of the two industries over the period. The average annualMAC are 11.82–25.55 CNY/ton across pilots, while the annual FCS demand expectation is 35 and 45 million tons for the thermal power and steel industries, respectively. If the MAC increases by 10%, the annual FCS demand will increase to 90 and 50 million tons, respectively. Other factors such as the prices of carbon emissions rights, carbon emission quotas, and industry output show little effect on FCS demand. Conclusion: The economic and technological efficiency of emissions reduction in different industries should be considered comprehensively, and that the consumer to producer subsidy for FCS in the carbon market should be adjusted for resource distribution optimization.

This would promote emissions reduction, stimulate FCS demand, and improve the carbon market mechanism.

Key words: carbon intensity; marginal abatement costs (MAC); forest carbon sequestration (FCS); tobacco industry

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China has the greatest tobacco industry all over the world.Tobacco leaf production and cigarette productionrespectivelyaccounts for about 35% and 32% of the world's total. There are 320 millionsmokers consuming 2 trillion cigarettes each year. The tobacco industry market size has reached 956.635 billion CNY in 2020. Compared with other heavy pollutionindustries, the carbon emission growth rate of the tobacco industry has decreased for many years, and the carbon emission is not in the forefront.Nevertheless, China's tobacco industry has still made steady progress inenergy saving and emission reduction.For example, the use of energy was 18.4 kg standard coal per 10,000 CNY industrial value added in 2015, decreasing 49.7% compared with 2000; 10,000 cigarettes consumed 2.95 kg standard coal in 2015, decreasing 49.7% compared with 2000. By 2020, the tobacco industryhas reduced energy consumption and CO_2 emissions per unit industrial added value by 15% and 18% respectively. These show theresponsibilityforemissions reductions from the tobacco industry[1].

For the tobacco industry, abatement cost varies under different emission reduction paths. The carbon emission trading market, especially the regulatory role of forest carbon sequestration(FCS) in this market provides a new opportunity for the tobacco industry to reduce emissions. Throughemissionstrading schemes (ETSs),the steel and thermal power industry has been forced into the market. Because they are high-polluting, high-emission industry, with relatively complete carbon verification and reporting systems. Therefore, this paper estimates the steel and thermal power industries' emission reduction costs to explore the FCS demand for these industries, which can provide useful reference and implications for China' tobacco industry to choose the path of emission reduction and consider the FCSinvestment to offset the carbon emission.

Market mechanism has been the main measure to control climate change for international society, and has created an important opportunity for China to participate in global governance and achieve the goals of reaching peak carbon emissions and carbon neutrality in the next few decades [2]. Meanwhile there are 158.94 million hectares of forests in China, which can generate carbon sequestration from the atmosphere. Hence, greater integration of forestry into the carbon emission trading market will be the innovation of the forestry ecological compensation mechanism, which not only promotes the flow of resources to green and low-carbonindustries, but also creates forest carbon sequestration (FCS) demand, making FCS industry become a new driving force for green economic growth.

Since 2011, China has conducted ETSs in seven provinces and cities, and has launched trading in the pilot carbon market since 2013. After the end of 2017, the pilot ETSs and the carbon market in the national power generation industry are in a parallel transition period[3]. The Chinese national emissionstrading scheme is a cap-and-trade (C&T) system that distributes free quotas to industrial enterprises according to benchmark method. Meanwhile, the Chinese Certified Emission Reduction (CCER) is involved in the carbon market as an improved and important supplementary mechanism of the C&T quota market [4]. In the short-term, the unified national carbon market will commence with the electrical power industry. In the long run, more and pollution industries will be gradually incorporated into the unified carbon market [4].

The technical costs for China's energy-intensive industries to reduce their carbon emissions can be high. For this reason, enterprises in these industries tend to choose lower cost options to alleviate the pressure of emissions reduction [5].

Reducing carbon emissions through participation in the forestry sector under market-based schemes is considered a cost-effective approach for addressing climate change impacts. Cost estimates vary for different energy-intensive industries. Hence, it is necessary to generate accurate calculation of the marginal abatement costs of CO_2 emissions (MAC) for different industries, and to better understand the demands for FCS [6-8].

In the context of the Chinese C&T system, evaluating the MAC under acarbon emissionspricingschemefor different industries would be a significant step towards achieving the country's emissions reduction targets[9-11]. However, there has been little research to compare the MAC of different industries and across different regions. In China, CO_2 emissions from the thermal power and steel industries account for 38% and 16% of the country's total emissions, respectively. These values far exceed the global average. In addition, the provinces and cities involved in China's seven pilot ETSs contribute about 11 trillion CNY to the national GDP (i.e., 30% thereof). The proportion of these provinces and cities is about 23%of the country's energy demand. And that's why it is essential to assess the MAC of steel and thermal power industries in the provinces and cities involved in China's seven pilot ETSs, and the demand for FCS in these locations [12, 13].

In different pilot ETSs in China, the thermal power and steel industries have always had different MAC for CO_2 emissions. However, just what are the costs associated with CO_2 emissions reduction in different energy-intensive industries under different pilot ETSs, and how have these costs changed in recent years? For the thermal power and steel industries, what is the possible FCS demand range to offset corporate CO_2 emissions? Further, what is theimplementationeffect of different policy tools on the FCS demand of these two industries? Based onthe aboveissues, the followingcontext systematically investigates the productivity, input factors, CO_2 emissions intensity, MAC, and FCS demand of China's thermal power and steel industries during 2005–2017, and quantifies the FCS demand level of these two industries in five scenarios.

LITERATUTER REVIEW

The MAC refers to the additional cost of one unit of carbon emissions reduction achieved by an enterprise that is implementing emissions reduction under the premise of no change in output [14]. In the framework of general equilibrium, the MAC is equal to the carbon shadow price. At present, the main tool for studying the MAC is marginal abatement cost curves (MACC). Many scholars have demonstrated the single increase convexity of MACC. That is, with an increase in reduced emissions, the cost of emissions reduction presents a monotonically increasing convex function [15, 16]. The research on MAC or the carbon shadow price has attracted increasing scholarly attention since the signing of the Kyoto Protocol in 1997 [17-20].

The existing literature on MAC calculation methods can be divided into different types, based on the estimation methods. The first type of research has used top-down macro-economic models, such as state-space, general equilibrium model and other econometric models. These models incorporate various emissions reduction constraints and set the model conditions to moderate the CO_2 emissions of high carbon production corporations [21-22]. The second category of research used bottom-up modeling methods, mainly relying on information technology. This approach constructs a dynamic model by setting up a variety of technical and economic indicators of energy, and then calculates the MAC of CO_2 emissions [23]. The third category combines the above-noted two models to conduct a comprehensive study of MAC. This research includes studies based on the MARKAL model, including the entire energy system which contains the production, processing and logistics of fuel resources, and the energy service demands from imports to domestic[24].

In addition to the above typical methods, the distance function, based on an input-output analysis, has emerged in recent years as another important approach to calculating the MAC of CO_2 emissions [17]. This alternative technique is not only applicable to macro-level MAC estimations (i.e., for industries, regions and countries), but also to micro-level estimations (i.e., for individual enterprises). The distance function includes two categories. One is the parameter method which requiresa specific function expression.For example, Lee and Zhang [25] use the parametric method to calculate the MAC of manufacturing industries in China andcalculatedthe average cost is 3.13 dollars/ton. The other is the non-parameter method which is much more popular in MAC calculations, especially the approach developed by Chung et al,who introducedthe directional distance function (DDF) [26]. The advantage of the DDF is its comprehensive consideration of "asdesirableoutputs rise, undesirableoutputs fall"[27].The DDF has been improved and is widely applied as a reckon method of the carbon shadow price and assessments of technical efficiency [28, 29].

After estimating the MAC of CO_2 emissions, some literatures have drawn conclusions about emission reduction efficiency or decisions. They indicate that enterprises can make more flexible choices (such as buying CCER in FCS programs) to offset carbon emissions. This paper emphasizes the potential demand of FCS by enterprises. The reasons are as follows: (1) China's abundant forests play an important role in achieving carbon neutrality in China, given to the carbon sequestration capacity of forests[30, 31]; (2) the material abatement effect of greenhouse gases or the carbon absorbing effect have been achieved through the FCS transaction [32]; (3) the FCS offset mechanism can not only alleviate the cost pressure of CO_2 emissions of enterprises [33], but can also realize the benefits of forest ecological value [34].

There are few studies on the demand potential of FCS. The literature in this domain includes questionnaire surveys and subjective evaluations, which focus on the value of FCS [35-37]. These studies are not based on the cost analysis of emissions reduction of enterprises, nor can it be closely combined with market factors. Therefore, it is difficult to accurately infer the overall FCS demand and analyze the policy effects. Accordingly, this study used a logistic algorithm to reflect the relationship among FCS demand, the MAC of CO_2 emissions, and other influencing factors. Further, literature on the policy simulation of the FCS demand is rare. While the cloud model has been gradually developed and used in time series prediction, risk assessment, and policy simulation [38, 39], it provides a simulation analysis tool for this study.

METHOD

Study sites

Seven ETS Pilot schemes differ in terms of economic structure and development. For instance, Guangdong, one of China's manufacturing hubs, is comparatively rich, while Hubei, one of China's car industry hubs, is less developed. But the seven pilots all include the power and steel industries. These pilots cover geographic areas exceeding 481 thousand Km^2, with a population of over 260 million people (around 18% of China's population) and GDP of almost 3.32 trillion dollars in 2017 (27% of China's GDP), and account for 20% of the energy consumption as well as 16% ofCO_2 emissions in China.Despite this, the carbon trading volume of these pilots reached 49.031 million tons of carbon dioxide equivalents in 2017. By 2020, there were 2837 key emission units, 1082 non-compliance institutions and 11169 natural personsparticipating in ETSs of China. Among them, there were some tobacco enterprises such as Shenzhen Tobacco Industry Co., Ltd. and Shanghai Tobacco Group Co., Ltd. The ETSs in China hasleapt tothe world's 2^{nd} largest carbon market, with 406 million tons of the cumulativecarbon quotas. And thus, it is typical and representativeto use the seven pilots as study sites.

Models

With the reduced scope for equipment renewals and technological innovations for reducing carbon emissions, enterprises will in future seek new emissions reduction modes under C&T systems. Whether China's thermal power and steel industries will generate a demand for FCS to offset their CO_2 emissions mainly depends on the MAC and FCS price in a reasonable C&T market. Therefore, investigating the MAC using panel data is particularly important.

Different from traditional production functions, the DDF represents a multi-output, multi-input production technology and it requires specification of direction vectorsto illustrate both output growth and input decline, which means that it contains the possible use of undesirableinputs or outputs. In optimal directions, latent prices for bad outputs can be estimated from the DDF, which can be used tomeasure behavioral response of economic subjects to shadow prices.Some relevant variablesare selectedfor the MAC estimation. The model takes industrial output value as the desirable output (marked as vector y) and CO_2 emissions as the undesirable output (marked as vector a), as well as three inputsincluding capital (vector k), labor (vector l), and energy (vector e). Finally, theproduction function can be represented by a set of possible outputsP(x) = {(y, a): x can produce (y, a)}.

Additionally, the emission reduction strategy direction vector b = (by – ba) has a proportional growth in industrial output and a reduction in CO_2 emissions. Compared with the production unit E(a, y), the desirable output increased by β1*ba and the CO_2 decreased byβ1*by. Moreover, another strategy is expanding the desirable output when the CO_2 emissions are fixed. Comparing the above two strategies, the former requires the business decision makers to give up their immediate interests. Therefore, the cost of carbon emissions reduction can be represented as Δy/Δa.

The DDF is shown as Equation 1. The direction vector f = (1, −1) has three meanings: the first one is that the desirableoutput increaseswhile the undesirable output decreases under the condition ofthe fixed inputs; the second is the simplification of estimating the unknown parameters; the third is matching the transfer property of the DDF.

$$\begin{aligned}&\vec{D}_0(x,y,a;f_y,-f_a)=\\&\max\left\{\alpha:(y+\beta f_y,a-\beta f_a)\in P(x)\right\}\end{aligned} \quad (1)$$

Furthermore, the specific form of DDF is shown as a quadratic function in Equation 2:

$$\begin{aligned}&\vec{D}_0(x_i,y_i,a_i;1,-1)\\&=\alpha+\sum_{n=1}^{3}\beta_n x_{ni}+\gamma y_i+\eta a_i+\frac{1}{2}\sum_{n=1}^{3}\sum_{n'=1}^{3}\alpha_{n,n'}x_{ni}x_{n'i}\\&=\frac{1}{2}\lambda y_i^2+\frac{1}{2}\theta a_i^2+\sum_{n=1}^{3}\delta_n x_{ni}y_i+\sum_{n=1}^{3}\omega_n x_{ni}a_i+\varphi y_i a_i\end{aligned} \quad (2)$$

To estimate all parameters in the DDF, many studies adopt to minimum deviationbetweenefficient production frontiers and decision-making units (DMUs). And thus, the target programming model can be depicted as follow ($i=1,2,\cdots,7$):

$$\min\sum_{i=1}^{7}\left[\vec{D}_0(x_i,y_i,a_i;1,-1)-0\right] \quad (3)$$

$$\text{s.t. } \vec{D}_0(x_i,y_i,a_i;1,-1)\geq 0 \quad (4)$$

$$\frac{\partial\vec{D}_0(x_i,y_i,a_i;1,-1)}{\partial a}\geq 0 \quad (5)$$

$$\frac{\partial\vec{D}_0(x_i,y_i,a_i;1,-1)}{\partial y}\geq 0 \quad (6)$$

$$\frac{\partial\vec{D}_0(x_i,y_i,a_i;1,-1)}{\partial x_n}\geq 0 \quad (7)$$

$$\begin{aligned}&\gamma\text{-}\eta\text{=-}1\quad \lambda\text{=}\theta\text{=}\varphi\quad \delta_n\text{=}\omega_n,\\&\alpha_{n,n'}=\alpha_{n',n},\quad n=1,2,3\end{aligned} \quad (8)$$

There are originally 24 parameters which to be estimated in Equations 3–8. And due to the direction vector f, the number of parameters reduces to 15.

Possible input and output vectors are described by P(x). The price vector of desirable and undesirable output are described byp = (p_1, . . . p_M) and q = (q_1, . . . q_J) respectively. The objective function of profit maximization is:

$$\begin{aligned}&R(l,p,q)\\&=\max_{x,y,a}\left\{py-qa-lx;(y,a)\in P(x)\right\}\\&=\max_{x,y,a}\left\{py-qa-lx;\vec{D}_0(x,y,a;f)\geq 0\right\}\end{aligned} \quad (9)$$

If (y, a) is on the production frontier (y, a) ∈ P(x),

$$\begin{aligned}&(y+\beta f_y,a-\beta f_b)\\&=\left\{\left(y+\vec{D}_0(x,y,a;f)f_y,a-\vec{D}_0(x,y,a;f)f_b\right)\in P(x)\right\}\end{aligned} \quad (10)$$

If equation (10) is true to (y, a), the equation can also be obtained after elimination of the inefficiency. The profit function can be indicated as:

$$R(l,p,q) \geq (py - qa - lx) + p\vec{D}_0(x,y,a;f)f_y + q\vec{D}_0(x,y,a;f)f_a \quad (11)$$

The equality can only be achieved when a DMU achieves the production frontier.

$$\vec{D}_0(x,y,a;f) = \min\left\{\frac{R(l,p,q)-(py-qa-lx)}{pf_y+qf_a}\right\} \quad (12)$$

According to the data envelope theorem, the MAC of the undesirable output is calculated as:

$$p_i = -p_{yi}\cdot\frac{\partial\vec{D}_0(x,y,a;1,-1)/\partial a}{\partial\vec{D}_0(x,y,a;1,-1)/\partial y} \quad (13)$$

Based on previous research about the factors affecting the FCS demand, a logistic algorithm is established to express the relationship among different factors, including the MAC of CO_2 emissions (p^i) and the FCS demand (d).

$$d = \frac{p_i(1+s_p)}{p_f(1+s_s)}\cdot\frac{1}{1+\exp\left[\sum_{i=1}^{N}TC_i(1+s_q)\div G_i(1+s_v)\right]} \quad (14)$$

In the above equations, p_f represents the average trading price of carbon emission rights in seven Chinese pilot studies. TC_i and G_i indicate the total annual carbon emissions and total annual output value of sector i. The remaining terms represent four factors affecting the FCS demand. It includes s_p (the penalty intensity of over-emission), s_s (the subsidy intensity of emissions reduction), s_q (the quota intensity of carbon emission), and s_v (the increasing rate of the output value).

This researchapplies the cloud model to simulate the FCS demand of the thermal power and steel industries in seven pilots, and to compare the impacts of different policy variables on the FCS demand. The cloud model belongs to the category of uncertain artificial intelligence, mainly used for the mutual transformation between qualitative and quantitative expression by cloud generator (GG). Clouds, or cloud drops, are the basic units of the cloud model. "Cloud" refers to a division of the domain that can be compared in the form of joint probabilities. The digital characteristics of the FCS demand especially the uncertainty could be represented by the cloud model which comprises a set of parameters (E_d, E_n, H_e). Expectation E_d is the typical sample point related to qualitative expression in the FCS demand. Entropy E_n indicates the concept of FCS demand, and hyper entropy H_e shows the uncertainty of entropy, which reveals the uncertainty, especially the relationship between random and fuzzy in the FCS demand.

The reverse cloud generator (GG-1) realizes the conversion from quantitative values to qualitative concepts. This implies that parameters (E_x, E_n, H_e) are obtained from a given cloud droplet sample (d_i) to realize the qualitative evaluation of the sample data. Given the uncertain information, the reverse cloud algorithm is as follows:

$$E_d = \frac{1}{n}\cdot\sum_{j=1}^{n}d_j \quad (15)$$

$$E_n = \sqrt{\frac{\pi}{2}}\cdot\frac{1}{n}\sum_{j=1}^{n}\left|d_j - E_d\right| \quad (16)$$

The sample variance S^2 is

$$S^2 = \frac{1}{n-1}\sum_{j=1}^{n}(d_j - E_d)^2 \quad (17)$$

If $S^2 \leq En^2$, then $H_e=(S^2-En^2)^{1/2}$; otherwise, delete the nearest 1% sample point from Ed in the current sample, use equation (17), and finally calculate the He to optimize the solution.

Datasets

Data of industrial energy consumptionwere extracted from the China Energy Statistical Yearbook (2006–2018). Data related to the labor force and industrial production was available from the statistical yearbooks of each of the seven provinces or cities (2006–2018) (industrial production is measured at a 2005 constant price). Capital stocks were estimated using the Perpetual Inventory Method. In addition, data for CO_2 emissions were not directly available from the statistical yearbooks. Following the Guidelines for

National Greenhouse Gas Inventories[40], we calculated the CO_2 emissions using Equation 18:

$$CO_2 = \sum_{j=k}^{n} a_k \cdot C_k \cdot E_k \cdot COE_k \tag{18}$$

where k (k = 1, 2, . . . , 6) means various types of fossil fuels. In order to avoid repeated calculations, besides three traditional fossil fuels, crude oil is divided into gasoline, diesel, kerosene and fuel oil. In Equation 18, a_k is the loss coefficient, C_k represents the consumption of fossil fuels, E_k is the standard coal conversion factor, and COE_k is the emissions coefficient.

The prices of carbon emission rights were derived from the official websites of exchanges in the pilot areas. The values of the scene variables, including the penalty intensity of over-emission, the subsidy intensity of emissions reduction, the quota intensity of carbon emission, and the increasing rate of the output value, refer to relevant documents of local environmental protection departments and the China National Development and Reform Commission (NBER).

RESULTS AND DISCUSSION

Carbon intensity

The results show that the carbon intensity differs greatly across the different study sites, and generally demonstrate a downward trend during the sample period (2005–2017) (Table 1). In 2017, CO_2 emissions per unit of GDP of the seven pilots declined by 54.06% in the thermal power industry and 56.05% in the steel industry, compared with 2005. According to the report from the 2017 COP24 conference in Katowice,China hadreducedCO_2 emissions per unit of GDP by 46% from the 2005 level, fulfilling its commitment to reduce carbon emissions by 40%–45% from the 2005 level by 2020.It can be inferred that the thermal power and steel industries in the pilots have made outstanding contributions to the national reduction of carbon intensity.

Table 1
Carbon Intensity of the Thermal Power and Steel Industry (tons/10,000 CNY)

Industry	Year	Beijing	Tianjin	Shanghai	Guangdong	Shenzhen	Hubei	Chongqing
thermal power	2005	0.84	3.70	0.55	1.29	1.09	7.76	7.73
	2006	0.59	2.29	0.49	1.19	1.18	7.07	7.54
	2007	0.45	1.87	0.45	1.01	1.10	7.48	7.38
	2008	0.41	1.44	0.41	0.99	1.37	6.01	5.80
	2009	0.40	1.69	0.42	0.91	1.13	4.50	5.10
	2010	0.31	1.75	0.37	0.88	1.20	5.50	4.49
	2011	0.33	1.66	0.34	0.78	1.12	6.09	4.45
	2012	0.26	1.41	0.34	0.81	1.30	4.68	3.28
	2013	0.23	1.51	0.34	0.76	1.41	6.22	3.35
	2014	0.20	1.52	0.34	0.69	1.40	5.92	2.81
	2015	0.17	1.50	0.40	0.67	1.38	5.51	2.69
	2016	0.15	1.51	0.42	0.64	1.50	5.72	2.53
	2017	0.13	1.43	0.34	0.62	1.52	5.69	2.36
	average	**0.34**	**1.79**	**0.40**	**0.86**	**1.28**	**6.01**	**4.58**
steel	2005	0.29	3.09	0.43	7.82	1.82	4.33	3.50
	2006	0.27	4.16	0.38	7.10	3.65	3.72	3.70
	2007	0.29	4.17	0.33	7.53	1.60	4.77	3.30
	2008	0.19	3.51	0.37	5.11	1.76	4.05	2.77
	2009	0.14	4.26	0.28	5.47	4.00	4.41	2.16
	2010	0.18	2.51	0.55	3.46	2.13	4.13	1.30
	2011	0.06	2.65	0.29	3.52	1.83	4.09	1.61
	2012	0.06	2.92	0.26	3.49	1.41	3.53	1.56
	2013	0.03	2.80	0.24	3.73	1.50	4.35	1.27
	2014	0.04	2.63	0.20	3.59	1.49	4.51	0.93
	2015	0.04	2.62	0.20	3.80	1.50	3.98	0.73
	2016	0.03	2.35	0.18	3.55	1.53	3.93	0.61
	2017	0.03	2.14	0.19	3.37	1.38	4.04	0.58
	average	**0.13**	**3.06**	**0.30**	**4.74**	**1.97**	**4.14**	**1.85**

From a sector perspective, regional differences in carbon intensity are greater for the thermal power industry. Emissions intensity is the lowest in Shanghai and Beijing, where the average annual carbon intensity is 0.40 tonsper 10,000 CNY and 0.34 tonsper 10,000 CNY, respectively. This differs dramatically from Hubei, where the average annual carbon intensity is over 4.00 tons/10,000 CNY, which is significantly higher than in the other pilot areas. A positive trend is that the CO_2 emissions per unit output value in these higher carbon intensity areas is significantly decreasing and the difference between different regions is declining. Despite this, there is growing pressure for further emissions reduction in the thermal power industry, and it is thus urgent for enterprises to purchase emission quotas or CCER credits such as FCS.

The carbon intensity of the steel industry is more convergent among regions. Shanghai has the lowest carbon intensity for the steel industry; this has declined from 0.535 tons/10,000 CNY in 2005 to 0.304 tons/10,000 CNY in 2017. Other regions exhibit relatively large interannual fluctuations—particularly Guangdong, Shenzhen, Hubei, and Beijing. In 2013 and 2014, with the establishment of pilot carbon trading markets, the carbon intensity declined to almost the lowest point of the sample period. This highlights the substantive role of carbon markets in promoting CO_2 emissions reduction.

The MAC

The MAC of CO_2 emissions are calculated based on the DDF model. The results illustrate clear differences in the MAC between the two industries, both across the study sites and during the sample period, due to varying environmental regulations, energy efficiency, and emissions reduction technology and associated management capacity.

To eliminate the effects of the interannual fluctuations, an average annual MAC is considered here (Table 2). In Shanghai, the average annual MAC of both the thermal power (11.94 CNY/ton) and steel industries (11.82 CNY/ton) is relatively low. In contrast, the average annual MAC in Guangdong and Shenzhen is higher than in other pilots. Shenzhen, in particular, have the highest average annual MAC among the seven pilots, namely 25.55 CNY/ton in the thermal power industry and 21.45 CNY/ton in the steel industry. Influenced by complex market factors, the MAC of CO_2 emissions and carbon intensities are somewhat disconnected. As Hubei and Chongqing with high carbon intensity in the economically less developed pilots, the MAC of CO_2 emissions has still not been as high as the pilots in the southeastern developed areas.

The MAC of the thermal power and steel industries generally increased with the establishment of ETSs in China in 2013 and 2014. With the tightening of the carbon emission quota, the MAC of CO_2 emissions will continue to rise; this is bound to lead to a greater demand for FCS in the above industries.

Table 2
The MAC of CO_2 Emissions for the Thermal Power and Steel Industries (CNY/ton)

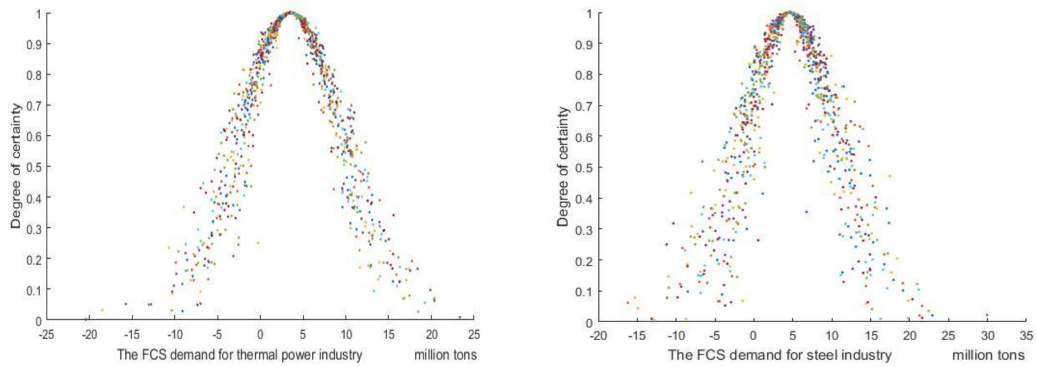
Industry	Year	Beijing	Tianjin	Shanghai	Guangdong	Shenzhen	Hubei	Chongqing
thermal power	2005	0.03	0.00	0.02	0.70	0.01	0.00	0.00
	2006	2.74	0.00	1.96	3.22	0.07	0.01	0.06
	2007	6.35	1.11	0.03	27.41	1.80	15.92	2.33
	2008	0.03	46.57	5.01	2.95	1.36	16.46	0.00
	2009	0.03	0.53	1.30	0.03	86.85	13.23	0.18
	2010	0.03	0.87	0.03	13.61	1.86	0.34	1.36
	2011	18.36	2.37	0.59	15.59	72.75	3.76	35.27
	2012	13.77	0.02	23.46	5.18	14.03	0.09	0.00
	2013	1.23	0.98	25.41	29.17	21.91	0.02	0.96
	2014	27.91	0.35	5.95	29.17	21.91	14.03	1.39
	2015	91.78	3.02	3.03	55.15	65.55	14.03	65.93
	2016	13.03	71.43	53.90	75.12	33.03	33.02	50.29
	2017	13.03	65.24	34.48	22.79	10.98	55.66	42.35
	average	**14.49**	**14.81**	**11.94**	**21.55**	**25.55**	**12.81**	**15.39**
steel	2005	2.04	1.25	0.03	2.44	0.71	41.86	0.01
	2006	42.53	0.01	0.09	0.00	1.30	0.04	34.17
	2007	24.14	57.82	0.02	0.32	10.25	0.00	3.58
	2008	0.01	67.26	0.42	53.73	43.73	19.15	0.48
	2009	68.36	1.65	0.68	0.29	0.03	0.13	0.12
	2010	0.03	5.60	0.03	0.01	1.71	0.97	35.93
	2011	0.07	22.52	0.02	20.98	0.74	0.13	1.19
	2012	0.67	14.02	0.93	92.41	0.02	2.32	1.72
	2013	1.08	1.62	65.46	17.64	16.68	0.00	16.46
	2014	39.31	34.14	40.31	1.06	70.54	54.65	83.24
	2015	25.34	18.17	11.08	46.29	10.43	54.65	19.88
	2016	13.67	19.29	11.08	5.65	75.98	4.97	6.23
	2017	33.30	17.39	23.56	20.30	46.71	30.30	27.38
	average	**19.27**	**20.06**	**11.82**	**20.09**	**21.45**	**16.09**	**17.72**

The demand for FCS

It is assumed that the over-emission penalty, the emissions reduction subsidy, the carbon emission quota, and the output value remain at the current level. Based on the MAC, the demand for FCS in the thermal power and steel industries is calculated through the logistic algorithm and cloud model.

The average concentration of cloud droplets is between 0-50 million tons. The cloud droplets are highly concentrated, with low dispersion and good overall stability. It illustrates the reliability of entropy and super-entropy (Figure 1). The annual demand expectation for FCS is 35 million tons in the thermal power industry and 45 million tons in the steel industry for all seven pilots. However, the annual demand expectation deviates substantially from the actual trading volume of FCS in the seven pilots. Hence, there is a huge demand for enhancement of FCS.

Figure 1
The FCS Demand in Thermal Power and Steel Industry



To improve the potential demand for FCS, this study simulated the annual demand potential for FCS under four scenarios. Different scenario designs and policy variables mainly refer to the practical experience and relevant policies of the pilot areas. Here, the penalty intensity of over-emission is reflected by the MAC of CO_2 emissions, and the subsidy intensity of emissions reduction is reflected by the prices of carbon emissions rights. The assumptions and results are shown in Table 3.

In scenario (1), the demand distribution of FCS, with an average of about 90 million tons, tends to the right as a whole; the deviation expands in thermal power industry. This implies that the increasing penalty intensity of over-emission obviously promotes the demand for FCS in the thermal power industry. If the MAC of CO_2 increases by 10%, the demand distribution of FCS is more concentrated, and its mean value decreases from 35 million tons to 15 million tons in the steel industry. In view of the different demand elasticity of FCS to the MAC of CO_2 emissions, it is essential to formulate the penalty intensity of over-emission by sub-sectors to stimulate the FCS demand with lower costs. The power generation industry has taken the lead in launching a national carbon emissions trading system in China since the end of 2017. This paper also proves that the FCS demand for the thermal power industry is significantly more than that for steel industry in the case of the MAC increase.

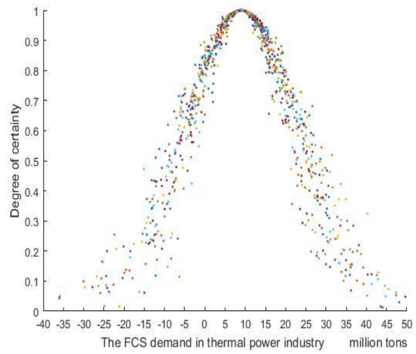
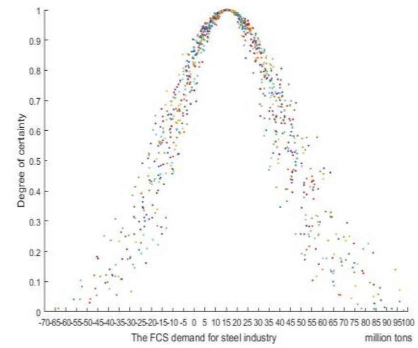
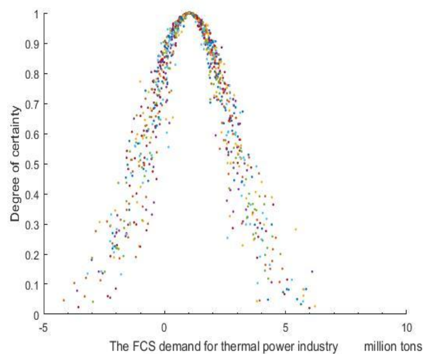
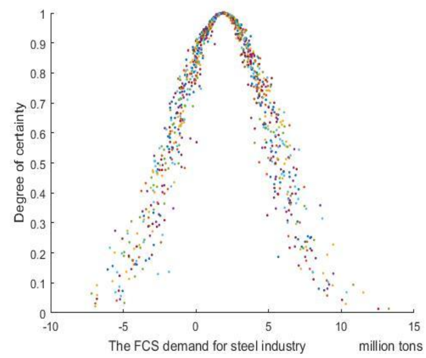
In scenario (2), if the subsidy intensity of emissions reduction is improved by 10%, the expectation for FCS will decline to concentrate on 20 million tons in both industries; the degree of discretization further decreases in the thermal power industry.

In scenario (3), the impact of the carbon emission quota's tightening on the demand for FCS is relatively limited, in spite of the latter's growth. The demand expectation is 38 million tons in the thermal power industry and 50 million tons in the steel industry when the carbon emission quotas decline by 10%. Further, the degree of discretization decreases in thermal power industry. The possible reason lies in abundant emission quotas during the initial stages of the domestic carbon market.

In scenario (4), the increases in industry output has no apparent significance on the FCS demand. When the industry output increases by 15%, the FCS demand expectation is approximately 30 million tons in the thermal power industry, and remains at 45 million tons in the steel industry. With industrial transformation and upgrading, the increase of the industry output mainly relies on the continuous elimination of backward production capacity, which reduces the pressure of emissions reduction and maintains the growth of FCS demand.

Table 3

FCS Demand under Four Scenarios

<table>
<tr><th>Scenario</th><th>FCS demand in the thermal power industry</th><th>FCS demand in the steel industry</th></tr>
<tr><td>(1) The MAC of CO_2 emissions increases by 10%.</td><td>
</td><td>
</td></tr>
<tr><td>(2) The prices of carbon emissions rights increase by 10%.</td><td>
</td><td>
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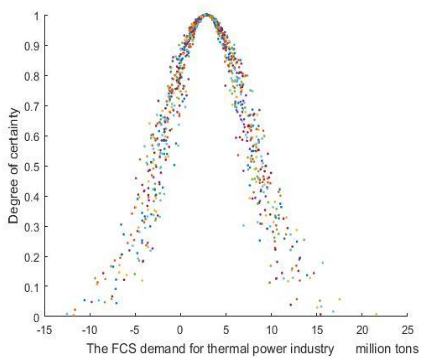
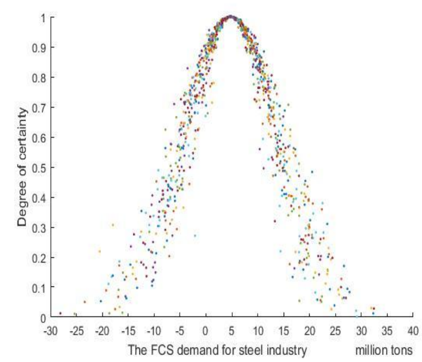
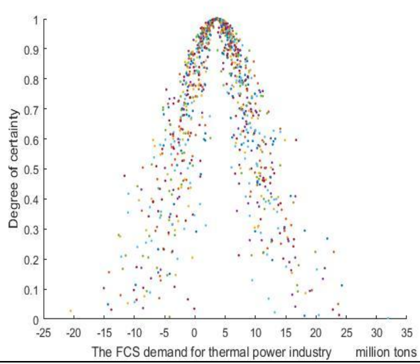
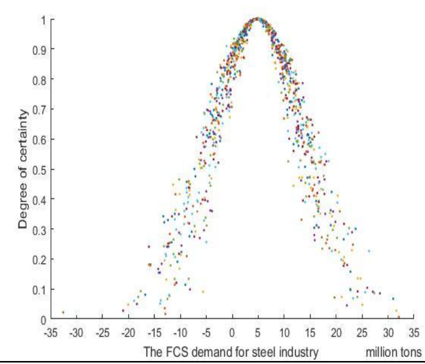
<tr><td>(3) Carbon emission quotas decline by 10%.</td><td>
</td><td>
</td></tr>
<tr><td>(4) Industry output increases by 15%.</td><td>
</td><td>
</td></tr>
</table>

CONCLUSIONS AND IMPLICATION

Conclusions

This paper compared the carbon intensity and calculates the MAC of CO_2 emissions of the thermal power and steel industries in seven pilots in China. The focus is on the estimation of the FCS demand based on the MAC of CO_2 emissions. Through a simulation analysis under different scenarios, this paper explored how different policy designs respectively affect the FCS demand in the thermal power and steel industries. Finally, it proved the relationship between these policy factors and FCS demand, and interpreted the demand mechanism of FCS. The conclusions are as follows.

First, the carbon intensities of China's thermal power and steel industries declined from 2005 to 2007 by an average of 55.6% and 56.6%, respectively. The carbon intensity decline is far ahead of the average level of all industries in China. Compared with the carbon intensity in the steel industry, the regional disparities of carbon intensity are more significant in the thermal power industry. Carbon efficiency is higher in economically developed areas. With the operation of the seven pilot ETSs, the regional disparities of carbon intensity are gradually decreasing, which pave the way for constructing a national carbon market across all industries and for achieving the peak CO_2 emission as soon as possible.

Second, the MAC of CO_2 emissions is somewhat unrelated to the carbon intensity of China's thermal power and steel industries. Although the MAC of CO_2 emissions is still lower than the current prices of carbon emission rights, resulting in the trade inactivity of the actual carbon market, the MAC of CO_2 emissions shows an upward trend in different pilots, unlike the downward carbon intensity trend. It reflects a certain pressure and constraints from the carbon market on industry emissions reduction. The free emission quotas will continue to decline as market policies improve and the industry transitions and upgrades. The MAC of CO_2 emissions will increase in future to force China's thermal power and steel industries to adopt carbon market offset mechanisms to meet their needs for carbon emission rights. This it is more likely to increase the FCS demand.

Finally, the FCS demand reflects an induced demand. Its value is realized through the carbon market mechanism. Among the carbon market factors, the MAC of CO_2 emissions, the price of carbon emission rights, the emission quota, and the industrial scale are the key factors that determine the FCS demand. It is estimated that the annual FCS demand for China's seven pilots is 35 million tons in the thermal power industry and 45 million tons in the steel industry. However, the actual FCS demand in the above two industries is far below the expected value because of the imperfect carbon trading market. If the MAC of CO_2emission is increased by 10%, the annual FCS demand of the thermal power industry in China's seven pilots will double from 45 million tons to 90 million tons. If the initial emission quotas allocated to the steel industry of the seven pilots are reduced by 10%, the FCS demand in the steel industry will increase from 45 million tons to 50 million tons. The effects of the emissions reduction subsidy and industrial output on FCS demand are not prominent. Therefore, in order to increase FCS demand, it is urgent to adopt different cap emission policies for different industries.

Implications

China's greenhouse gas emission accounting methods and reporting guidelines for tobacco industry have been issued, which not only provides an important basis for the tobacco industry to enter the carbon emission trading market, but also provides a data base for further measuring the carbon intensity and marginal emission reduction costs of the tobacco industry. Although this paper is a comparative study of carbon intensity and marginal emission reduction costs in the steel and thermal power industries, the conclusions of the study also have the following policy implications for tobacco industry from the perspective of promoting the demand increase of forest carbon sequestration.

(1) The penalty for exceeding emission is adouble-edged sword. The increased penalty intensity may not necessarily transform into FCS demand, while increasing the pressure to reduce emissions. Therefore, it is essential to take into consideration the economic and technological efficiency of emissions reduction in different industries and to

impose different penalty intensities for different industries, in order to promote emissions reduction as well as stimulate the demand for FCS.

(2) Increasing the trading price of carbon emission rights is actually a subsidy of emissions reduction for the thermal power and steel industries. While there is still room for emissions reduction, the increase in the trading price encourages emissions reduction by the above industries and reduces their use of offset mechanisms, thus lowering the FCS demand. If the subsidy is used to purchase the FCS rather than to reduce emissions, it represents an adjustment of the consumer to producer subsidy for FCS in the carbon trading market. This is better aligned with China's current carbon trading market structure and may stimulate the FCS demand.

(3) Tightening the emission quota could indeed enhance FCS demand. However, in the context of China's industrial transformation and upgrading, the allocation of the emission quota is very important, since it determines how to maintain industrial development while reducing the total amount and intensity of carbon emissions and improving the FCS demand. As a means of macro control, the initial allocation and the reduction rate of the emission quota need to balance efficiency and equity as well as the economic and environmental benefitsin different regionsanddifferent sectors.

(4) The increase in industry output will not lead to a large increase in FCS demand. Under the increasingly stringent regulations of environmental protection, an increase in industry output is accompanied by lower energy consumption and lower emissions. Hence, the increasing output industry is more competitive in the carbon trading market. With industrial development, it is suggested that carbon asset management is strengthened, and investments are made in the FCS. This will not only increase the demand for FCS, but also help to promote the transformation of the real economy to a low-carbon economy through carbon financial transactions, and to accelerate the adjustment of the Chinese economic structure.

Conflict of Interest Disclosure Statement

This research is not funded by any organization related to tobacco production.

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