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What is the potential impact of a taxation system reform on carbon abatement and industrial growth in China?

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ABSTRACT

Economists have long argued that market-based environmental policy such as an environmental tax is beneficial to abate pollution emissions. This study aims at investigating the impact of carbon tax levy on carbon dioxide (CO_2) abatement and industrial growth in China. To this end, the marginal abatement cost (MAC) of industrial CO_2 emissions is estimated as the benchmark of setting the carbon tax rate by using the directional distance function (DDF). This paper employs the polynomial dynamic panel model to forecast the impact of carbon tax levy on target variables such as sectoral value-added and CO_2 intensity. The results reveal that the levy of a CO_2 tax has a negative impact on industrial output only in the short term. In the long term, the impact of CO_2 tax levy on output will become positive. The levy of a CO_2 tax is always beneficial to reduce CO_2 intensity. Corresponding policy suggestions for an environmental taxation system reform are given in the concluding section.

1. Introduction

To transform the economic development model and challenge global warming, in November 2009 the Chinese state council decided to abate CO_2 emission per GDP, namely CO_2 intensity, by 40–45% until the year 2020 as opposed to the benchmark level in 2005. This is the first time for China to officially release such quantitative carbon abatement goals. Though it is only relative carbon abatement rather than the absolute reduction employed by most other countries, it is still challenging for China to realize due to the country's coal-oriented energy consumption structure, its extensive

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factor-driving growth model, and so on. Now, the question is how to reform the traditional regulatory environment policy in China in order to successfully realize the new carbon intensity goal.

Traditional environmental policy is normally implemented through the administrative fiats in China. However, economists have long argued that environmental policy must be based more firmly on the use of market-based mechanisms so as to introduce the cost of pollution clearly into economic analysis and impose ceaseless price pressure on the polluters to reduce pollution (Bailey, 2002). Environmental tax and emission right trade are the main instruments of market-based environmental policy, based on the Pigovian Tax and Coase Theory, respectively. Environmental tax, also referred to as ecological or green tax, was first proposed by the British economist Pigou in his book on Welfare Economics, published in 1920. The central idea is to levy a tax on pollution emissions that have a negative externality so as to accurately reflect the social cost of production and internalize the cost into the market price. The tax on a negative externality is termed Pigovian tax and should equal the marginal damage costs. The environmental taxation reform may be understood as a reform process from a sub-optimal taxation system to an optimal one by continuously adjusting or removing the tax distortion effect. It is becoming the issue of a heated debate in the field of international environmental policy (Bosquet, 2000; Patuelli et al., 2005).

Environmental taxes levied in advanced countries, including energy tax, carbon tax, sulfur tax, water pollution tax, solid waste tax, noise tax, etc., have already played an important role in promoting sustainable development, which provides a positive experience of environmental tax reform for China. In fact, as far as known, environmental measures are implemented mainly by collecting pollution fees and less by tax in China. The few taxes are scattered in resource tax, consumption tax, value-added tax, vehicle and vessel tax, etc., and there is no precisely defined environmental tax (Andrews-Speed, 2009). For example, pollution charges have been collected in China since 1982 and currently attain an annual amount of RMB 20 billion yuan, which is just the actual cost of dealing with pollution without including external environmental cost. The resource tax already levied in China serves only to adjust the resource differential income, and does not correlate much with environmental protection. The situation shows the urgency of an environmental taxation reform in China. Of course, this is not to say that such a regulatory environment policy carried out in China is anything but effective. The country achieved a sustained decline of energy intensity in the period 1980–2001, with the largest decline between 1997 and 2001, corresponding with the ownership right reform which then caused the first reduction of total energy consumption accordingly, but this trend is reversed from 2002. Exemplified by the absolute change in CO_2 emission reported in Table 1, relative to the positive growth for almost all industrial sectors between 1981 and 1995, there are 32 sectors among all 38 samples that decreased their CO_2 emissions in the period of the 9th Five-Year Plan. In the same period, the averaged annual output growth attained 12.7%, much greater than the 7.6% averaged over the period 1981–1995. The number of sectors that reduced CO_2 emissions fell to only 9 in the period of the 10th Five-Year Plan (2001–2005) and 6 during the 11th Five-Year Plan (2006–2010).

Factors like the rapid urbanization and industrialization and the update of the consumption structure driven by the fanatical expansion of the housing and car industries attribute to the reappearance of heavy industrialization in China. In 2007, China became the largest emitter of CO_2 in absolute terms in the world, which puts China under continuously increasing pressure from the rest of the world to abate carbon emissions. Though inconsistent with the WTO rules and the spirit of the Kyoto Protocol, there exists the possibility that the developed countries will impose carbon tariffs on imports from countries without mandatory carbon abatement. In this case, as an example of an environmental tax, the levy of a carbon tax is more urgent than other kinds of environmental taxes in China and could be appropriately regarded as a first step to reform the traditional environmental taxation system. Though a carbon tax has been levied in such countries as Finland, Sweden, Norway, the Netherlands, Denmark, and others and performs well in those countries, it is still necessary to analyze its economic and environmental effect in the foreseeable future in China, which is particularly useful for environmental policymakers even though the theoretical foundation of environmental taxation is solid enough. This is the motivation of this study. This paper concentrates on the industry in China because its output, energy use and carbon emission account for most of the state level. In addition, as Jorgenson and Stiroh (2000) denoted, it is essential to disaggregate analysis to the sectoral level to find the true pattern behind the aggregation. Following this, the paper avoids the limitations of

Table 1
The sectoral change of CO_2 emissions for different Five-Year Plans (10,000 tons).

Sectors	6–8th Plan (1981–1995)	9th Plan (1996–2000)	10th Plan (2001–2005)	11th Plan (2006–2010)	Sectors	6–8th Plan (1981–1995)	9th Plan (1996–2000)	10th Plan (2001–2005)	11th Plan (2006–2010)
Coal	7607	−3076	12,658	17,907	Chemical Products	13,292	−3414	10,600	8446
Petroleum Ext.	5217	5340	−6131	363	Medicine	1298	−817	159	244
Ferrous Mi.	69	−57	91	82	Fibers	2330	273	228	−2255
Non-Ferrous Mi.	160	−192	15	3	Rubber	608	−632	238	178
Nonmetal Mi.	596	−77	338	312	Plastic	459	−349	186	414
Wood Exp.	123	−215	−55	−20	Nonmetal Ma.	17,600	−6880	13,862	15,565
Food Proc.	2272	−816	−387	1100	Ferrous Press	13,566	−3550	16,059	19,543
Food Ma.	1382	−1199	439	433	Non-Ferrous Press	1838	−310	2147	1321
Beverage	1289	−803	220	207	Metal Products	426	−486	119	154
Tobacco	268	−144	−15	−40	General Machinery	−53	−957	49	246
Textile	2187	−2479	1621	400	Special Machinery	237	−697	325	322
Apparel	163	−11	160	39	Transport Equipment	305	−395	241	409
Leather	297	−346	41	5	Electrical Equipment	324	−333	−62	937
Wood Proc.	361	−302	276	195	Computer	3	−97	172	64
Furniture	49	−47	−24	10	Measuring Instrument	58	−83	−17	16
Paper	2625	−816	2594	2232	Electric Power	61,315	22,160	99,694	97,448
Printing	33	−79	−16	10	Gas Prod.	532	614	595	−5
Cultural Articles	40	−34	1	5	Water Prod.	58	11	−23	−16
Petroleum Proc.	26,740	11,500	55,099	51,354	Others	646	−1268	423	−134

an aggregation analysis by breaking the Chinese industry down into 38 two-digit sectors in the period 1980–2010.

To analyze the potential impact of environmental taxation, the natural problem is how to set the appropriate tax rate. The optimal tax rate should equal the marginal abatement cost (MAC) or shadow price of environmental pollution (Bovenberg and Goulder, 2002; Zhang and Baranzini, 2004). However, due to the lack of a market price of pollution emission, the measure of abating cost and pollution price has been one of the greatest challenges in environmental economics. Following Boyd et al. (2002), this paper will estimate the sectoral MAC of CO_2 emissions over the entire reform period by comparing two versions of the Directional Distance Function (DDF) and using them as the basis of an industrial carbon tax rate to further evaluate the influence of carbon tax levy on economic and environmental variables such as industrial value-added and CO_2 emission intensity. The rest of this paper is structured as follows. Section 2 will survey the literature that studies the influence of environmental taxation, particularly carbon taxation, on economy and environment. Section 3 describes the two-stage analytical framework to satisfy the research purpose of this paper, that is, two alternative DDFs used to measure the MAC of carbon emission at the first stage and a polynomial dynamic panel model to evaluate the foreseeable effect of a carbon tax on economy and environment at the second stage. Sections 4 and 5 discuss the varying patterns of measured MAC and the influence of environmental taxation on target variables. Concluding remarks are presented in Section 6.

2. Review of the literature

The discussion on environmental taxation reform was originally initiated by Tullock (1967), who suggested that environmental taxes must be levied in order to ensure the optimal utilization of natural resources. The concept has been pushed further in Terkla (1984) and Lee and Misiolek (1986), even including an estimation of the optimal tax rate. Patuelli et al. (2005) analyzed a large set of applied studies and offered a quantitative comparative study of the estimated performance of environmental tax policies based on meta-analytical principles. Though an environmental tax may damage the economy, economic theory suggests that an environmental taxation reform might in fact bring about a double dividend (DD), i.e., the joint occurrence of a cleaner environment (the first dividend) and an economic improvement (the second dividend) under certain conditions (Pearce, 1991; Bovenberg and De Mooij, 1994). There is no standard definition of DD in the literature. For instance, the economic dividend is defined as the growth of employment or productivity by Carraro et al. (1996) and Jansen and Klaassen (2000), the effect of income distribution due to the change of salary or expenditure by Barker (1997) and Ekins and Speck (2000), fiscal benefits by Morris et al. (1999), economic growth represented by GDP and consumption by Garbaccio et al. (1999), and the increase of output and economic welfare by Jorgenson and Wilcoxen, 1993 and Peretto (2009). Bossier and Bréchet (1995) and Baranzini et al. (2000) describe the economic effect of an environmental tax as the rise of currency inflation. Even though based on the same definition, different influential factors are likely to cause inconsistent conclusions in the applied literature. In addition, by using the computable general equilibrium (CGE) model, Van Heerden et al. (2006) found that an ecological tax reform could lead to a triple dividend of reduced emission, increased output and shrinking income inequality.

Many papers have specifically discussed the relationship between carbon tax and the economy. Brännlund and Nordström (2004) argued that the overall welfare effects due to the carbon tax in Sweden, which has been in existence since 1991, are negative. Zhang and Baranzini (2004) assessed the main economic impacts of carbon taxes. Based on a review of empirical studies on existing carbon/energy taxes, it was concluded that their competitive losses and distributive impacts are generally not significant and definitely less than often perceived. Floros and Vlachou (2005) evaluated the impact of a carbon tax on energy-related CO_2 emissions in the two-digit manufacturing sectors of Greece based on the two-stage translog cost function. A carbon tax of \$50 per ton of carbon resulted in a considerable reduction in direct and indirect CO_2 emissions from their 1998 level, which implies that a carbon tax on Greek manufacturing is an environmentally effective policy for mitigating global warming, although a costly one. Scrimgeour et al. (2005) used a CGE model to assess the effect of environmental tax, in particular carbon and energy taxes, on the economy in New Zealand and concluded that a carbon tax reduces carbon emissions more effectively than an energy tax but adversely affects GDP. Wier et al. (2005) found that the carbon tax on income distribution in Denmark is negative, especially to the weak groups in the countryside. Based on a CGE model, Fisher-Vanden and Ho (2007) found that imposing a carbon tax on the price of energy will result in two broad impacts on the economy: factor substitution (causing firms to substitute away from energy toward other factors of production) and output substitution (causing consumers to shift consumption toward less energy-intensive goods). Wissema and Dellink (2007) used a CGE model to quantify the impact of the implementation of a carbon tax on the reduction of CO_2 in Ireland. They confirmed that the reduction target of 25.8% for CO_2 emissions in Ireland compared to 1998 levels can be achieved with a carbon tax of 10–15 Euros per ton of CO_2. Callan et al. (2009) analyzed the income distribution effect of the carbon tax in Ireland and concluded that a carbon tax is regressive in the sense that, in absolute terms, a carbon tax of 20 Euros per ton of CO_2 would cost the poorest households less than 3 Euros each week and the richest households more than 4 Euros per week. Kuosmanen et al. (2009) also employed a two-stage analytic method in which the shadow price of pollution emission is estimated first and then an environmental cost–benefit analysis (ECBA) is utilized to investigate the influence of different emission abatement policies on the economy. For others, see Nakata and Lamont (2001), Bruvoll and Larsen (2004), Kahn and Franceschi (2006), Voorspools and D'haeseleer (2005), Lee et al. (2007), and Kerkhof et al. (2008), to name a few.

There is also a literature studying carbon taxes in China. For example, He et al. (2002) analyzed the influence of a carbon tax on the Chinese economy by using the input–output table from 1997 and a CGE model. Their results showed that the levy of a carbon tax influences GDP very little and will reduce coal production and energy consumption and lead to an increase of coal and petroleum prices. By checking the impact of a carbon tax under three scenarios also based on a CGE model, Wei and Glomsrod (2002) found that a carbon tax will worsen economic growth but reduce CO_2 emission in China. Liang et al. (2007) simulated the impact of different carbon tax designs on the macroeconomy and energy-intensive sectors in China. Wang et al. (2009) argued that a low-rate carbon tax was a feasible option in China's near future. Lower carbon tax rates have a smaller influence on China's economic development but can lead to obvious CO_2 emission reductions. As can be seen from the above review, many papers use a CGE model to study the influence of environmental taxes on economy and environment. When using a CGE model, the carbon tax rate is often set under several fixed scenarios, but in this paper, the DDF model can help estimate the panel of the carbon tax rate. In addition, if the input–output table is only available at several discontinuous time points, a CGE model is undoubtedly an appropriate approach to deal with the limited data; if panel data exists, like the data in this paper for 38 sectors over a continuous time period from 1980 to 2008, a panel data model will be a more appropriate approach than a CGE model. Therefore, a two-stage analytical framework, which we will introduce in Section 3, will be adopted in this study. In brief, at the first stage, the sectoral MAC of CO_2 emission over the entire reform period is estimated by using two versions of DDF, which will be used to forecast the carbon tax rate likely to be levied in the foreseeable future; at the second stage, a polynomial dynamic panel data model (PDPDM) is employed to fit the historical relations between MAC and industrial value-added or CO_2 emission intensity, and to further evaluate the influence of carbon tax levy on the economic and ecological variables.

3. Two-stage analytical framework

3.1. Directional distance function and marginal abatement cost

Not until the presence of a directional distance function (DDF) do we find a reasonable framework to differentiate the desirable and undesirable outputs. More explicitly, different from other methods such as CGE, the DDF approach can capture the characteristics of negative externalities of undesirable outputs like environmental pollutions. Färe and Grosskopf (2000) prove that the DDF is dual to the profit function and provides the basis for computing the shadow prices, or MAC, of outputs. At the first stage, mainly following Boyd et al. (2002), two versions of DDF will be used to measure the MAC of undesirable CO_2 emission. See Fig. 1 for its principles.

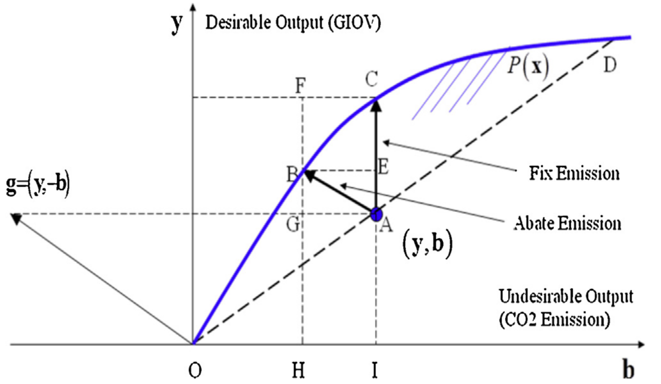

Fig. 1. The principle of the directional distance function.

Assume that there are n decision-making units (DMU) at time point t, and there are k types of input, l types of desirable output, and m undesirable output for each DMU. For the ith DMU ($i = 1, 2, \ldots, n$), the column vectors $\mathbf{x}_i$, $\mathbf{y}_i$ and $\mathbf{b}_i$ represent the inputs, desirable and undesirable outputs, respectively. $\mathbf{X}_{k\times n}$, $\boldsymbol{Y}_{i\times n}$ and $\mathbf{B}_{m\times n}$ are the input and output matrix for all n DMUs. As illustrated in Fig. 1, the technology is represented by the output set $P(\mathbf{x})$, to which the output vector of A point $(\mathbf{y}, \mathbf{b})$ belongs. In this study, the DMU is a two-digit sector in industry; for each of them, $k = 3$, corresponding to capital, labor and energy, $l = 1$ being gross industrial output value (GIOV), and $m = 1$ carbon dioxide emission (CO_2).[1]

To make it possible to model the increase of desirable output and the reduction of undesirable output simultaneously, Chambers et al. (1996) and Chung et al. (1997) first put forward the weak disposability assumption of undesirable output-based standard DDF (from point A to B in Fig. 1) to replace the traditional Shephard distance function (SDF, which radially scales the original vector from A to D to describe the simultaneous increase of desirable and undesirable outputs) proposed by Färe et al. (1994) and Boyd and McClelland (1999). That is,

$$\vec{D}_o^t(\mathbf{x}_i^t, \mathbf{y}_i^t, \mathbf{b}_i^t; \mathbf{g}_i^t) = \sup\{\beta : (\mathbf{y}_i^t, \mathbf{b}_i^t) + \beta\mathbf{g}_i^t \in P^t(\mathbf{x}_i^t)\} \tag{1}$$

in which β is the maximum feasible expansion of desirable output and contraction of undesirable output when the expansion and contraction are identical proportions for a given level of inputs, which amounts to the value of DDF to be measured. The notation $\mathbf{g}$ represents the direction vector and $\mathbf{g} = (\mathbf{y}, -\mathbf{b})$ for standard DDF, used to model the increase of desirable output and the reduction of undesirable output simultaneously. Thus, the DDF is also referred to as the activity analysis model (AAM) in the literature. If we let $\mathbf{g} = (\mathbf{y}, \mathbf{b})$, DDF will reduce to SDF, indicating SDF is just a special case of DDF.

More specifically, for the ith sub-industry, the standard DDF can be estimated by resolving the following linear programming (LP),

$$\begin{aligned} &\vec{D}_o^t(\mathbf{x}_i^t, \mathbf{y}_i^t, \mathbf{b}_i^t; \mathbf{y}_i^t, -\mathbf{b}_i^t) = \mathrm{Max}_{\lambda,\beta}\beta \\ &\text{s.t. } \mathbf{Y}\boldsymbol{\lambda} \geq (1+\beta)\mathbf{y}_i; \quad \mathbf{B}\boldsymbol{\lambda} = (1-\beta)\mathbf{b}_i; \quad \mathbf{X}\boldsymbol{\lambda} \leq \mathbf{x}_i; \ \boldsymbol{\lambda} \geq 0 \end{aligned} \tag{2}$$

The inequality for desirable output and inputs in LP (2) makes them freely or strongly disposable. Undesirable output is modeled with equality, which makes it weakly disposable. The intensity variable $\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \ldots, \lambda_n)^T$ contains the weight assigned to each sector when constructing the production frontier. The production frontier defined by the combination of input and output matrix $(\mathbf{X}, \mathbf{Y}, \mathbf{B})$ will be used as the benchmark to evaluate the efficiency of the ith DMU, $(\mathbf{x}_i, \mathbf{y}_i, \mathbf{b}_i)$.

To measure the MAC of undesirable output like CO_2 emission, Boyd et al. (2002) and Jeon and Sickles (2004) define another DDF, or the variation of standard DDF (from point A vertically to C in

[1] Though CO_2 is exemplified, the analytical framework introduced below could be easily extended to the analysis of other pollutions.

Fig. 1), which tells us the degree to which desirable output can be expanded, given inputs and undesirable output levels. It can also be referred to as fix emission based DDF, as shown in Fig. 1, which is computed by resolving the following linear programming (LP),

$$\begin{aligned}&\vec{D}_o^t(\mathbf{x}_i^t, \mathbf{y}_i^t, \mathbf{b}_i^t; \mathbf{y}_i^t, 0) = \mathrm{Max}_{\lambda,\beta}\beta \\ &\text{s.t. } \mathbf{Y\lambda} \geq (1+\beta)\mathbf{y}_i; \quad \mathbf{B\lambda} = \mathbf{b}_i; \quad \mathbf{X\lambda} \leq \mathbf{x}_i; \ \boldsymbol{\lambda} \geq 0\end{aligned} \tag{3}$$

The DDF modeled by LP (3) is consistent to what is proposed in the Kyoto Protocol, which controls CO_2 emission at the 1990 level, and also for the case of the carbon emission quota. The comparison of two alternative DDFs can estimate the MAC of CO_2 emission. Let the value of LP (2) and (3) be β_1 and β_2, respectively. Then $GB = \beta_1\mathbf{y}$ and $GA = \beta_1\mathbf{b}$ are the solution to LP (2), while $AC = GF = \beta_2\mathbf{y}$ corresponds to the fix emission based DDF. The difference labeled $BF = (\beta_2 - \beta_1)\mathbf{y}$ is the additional output that is foregone to reduce the emission by $\beta_1\mathbf{b}$. Therefore, the ratio of $(\beta_2 - \beta_1)\mathbf{y}$ to $\beta_1\mathbf{b}$ will tell us how much GIOV is given up for a unit reduction in CO_2 emission, which can be used to measure the MAC of CO_2 emission and approximate the shadow price of CO_2 (unit in this paper: RMB ten thousand yuan/ton of CO_2). Since there is no market price for CO_2 emission, measuring the MAC of CO_2 emission is important for policymakers, particularly when setting the appropriate carbon tax rate.

3.2. The polynomial dynamic panel data model and forecasting scheme

At the second stage, the MAC of CO_2 emission measured at the first stage will be used as the benchmark of the policy variable (*PV*), i.e., carbon tax. To analyze the influence of environmental taxation reform on the economy and the environment, we first fit the historical relationship between *PV* and the target variable (*TV*) and then, based on the estimated model, forecast the future trend of *TV*. The estimating and forecasting model used in this paper is the polynomial dynamic panel data model (PDPDM) specified below,[2]

$$\ln TV_{it} = \beta_0 + \beta_t t + \beta_{lag}\ln TV_{i,t-1} + \beta_1 \ln PV_{it} + \cdots + \beta_n \ln^n PV_{it} + u_i + \varepsilon_{it} \quad (n \leq 5) \tag{4}$$

in which *TV* and *PV* take the form of natural logarithms. The inclusion of a dynamic term, i.e., the lagged dependent variable ln*TV*_lag1, as the independent variable extracts the entire history of the right hand side variables on which all the results are conditionally based; in this case, the *PV* of carbon tax and its higher-degree terms, of special concern for this paper, represent the current shock of new policy information. The notation of u_i controls for heterogeneous characteristics and t captures the time trend of most sectors influenced by some general economy-wide factors such as the common macroeconomic policy and environmental regulations, which represent the "mushroom" and "yeast" effects of the target variables vividly described in Harberger (1998). The stochastic disturbance ε_{it} is assumed to follow the normal distribution of white noise.

In both the fixed and random effects settings, the difficulty is that the lagged dependent variable is correlated with the disturbance, even if it is assumed that the disturbance is not itself autocorrelated. There also exists possible endogeneity for *PV* and its higher degree terms because *PV* is also constructed by the desirable and undesirable outputs using the DDF approach. To control for the possible endogeneity, the Hausman and Taylor Instrumental Variable method (HT/IV) is chosen to estimate PDPDM (4). It is possible to estimate the time invarying variable u_i while still maintaining the assumption that the sectoral effect is correlated with the explanatory variables. Another method of System GMM proposed by Arellano and Bover is also employed to estimate PDPDM (4) for the robustness check. According to the review in Section 2, the target economic and environmental variables chosen in this paper are industrial value-added and CO_2 emission intensity, the former of which is the preferable growth indicator in the developing countries and the latter the relative carbon abatement indicator formally employed by the Chinese government.

The period in which the target variables are forecast under the scenarios of carbon tax levy is from 2011 to 2020, which is the span for the 12th and 13th Five-Year Plans and the time to realize the officially proposed carbon abatement goal. To forecast the dependent variable, the explanatory

[2] Gao et al. (2004) once used the quadratic polynomial model to fit the relationships between MAC and abating rate.

variables of carbon tax rates in the following years are first forecast according to the historical values of MAC estimated over 1980–2010 by adopting the time trend quadratic polynomial model. When forecasting the dependent variable, the one-year-ahead short-term recursive forecasting scheme is employed with an updating sample window. Specifically, the first estimating period is from 1980 to 2010 and the value of *TV* of 2011 could be forecast based on the estimated Eq. (4); the estimating and forecasting process is carried out recursively by updating the sample with one observation each time. The last estimating period is from 1980 to 2019 and the value of *TV* of 2020 will be forecast last. Thus, 10 one-period-ahead forecasting values of *TV* over 2011–2020 are obtained. As a polynomial model, of course the appropriate degrees of Eq. (4) must be chosen in advance for different dependent variables to avoid the possible overfitting problem. Following Chen et al. (2010), we divide the sample into two parts: training sample and validating sample. Based on the training sample and the short-term recursive forecasting scheme described previously, we could forecast the value of *TV* corresponding to the validating sample for polynomial models from first to fifth degree, and then calculate five mean absolute forecasting errors (MAE). Here, the first training sample spans from 1980 to 2005 and the last from 1980 to 2009. The validating sample corresponds to 2006–2010 and 38 sectors each year, including 190 observations in total.

To test for the forecasting accuracy of polynomial models for different degrees, we use the two-sided DM test statistic proposed by Diebold and Mariano (1995) for the difference of the MAE loss function. The null hypothesis is H0: MAE1 − MAE0 = 0, where the subscript 0 denotes the benchmark model and 1 the target model. The DM tests in this study are investigated in a robust form by simply scaling the numerator by a heteroscedasticity and autocorrelation consistent (HAC) (co)variance matrix calculated according to Newey-West procedures (Newey and West, 1987). We use Andrews' (1991) approximation rule to automatically select the number of lags for the HAC matrix. In the case of a large sample, the DM statistic converges to a standard normal in distribution. Based on the MAE and the DM test, the appropriate degrees of polynomials with the best generalization ability and out-of-sample performance can be determined to meet different dependent variables when using Eq. (4).

4. Measures of the marginal abatement cost for industrial carbon dioxide

As denoted in Section 3.1, the variables used in the empirical work include the gross industrial output value, industrial value-added, carbon dioxide emission (CO_2), labor force, capital stock and energy consumption. The construction of the data in this paper for 38 industrial sectors between 1980 and 2010 is described in the appendix. Table 2 reports the fitted and forecasted MAC of CO_2 emission averaged during periods of different Five-Year Plans for 38 sectors, light and heavy industry, and the aggregated industry in which the weight is the sectoral GIOV share. As in Chen et al. (2011), the light and heavy industry is classified according to the sectoral ranking of the capital to labor ratio from lowest to highest in 2004, in which the former 19 sectors with a lower capital to labor ratio are classified into the light industrial group and the second half of sectors with a higher ratio belong to the heavy industry.[3] However, sometimes the observation of the difference between the light and heavy industry is enough for the analysis because 38 sectoral patterns of MAC are too complicated to see clearly all at once.

As can be seen from Table 2, on average, the forecasted MAC of CO_2 emissions for the aggregated industry is 2731 and 4012 yuan per ton of CO for the 12th and 13th Five-Year Plan, respectively. MAC represents the internal valuation of pollution emission by societies, in which the pollution with more negative externality should be valued more. Thus, CO_2 is expected to have the lowest (by absolute value) MAC, nitrogen oxides (NO_2) to have the highest one, and sulfur dioxide (SO_2) to be somewhere in between. The averaged shadow price of industrial SO_2 estimated by Tu (2009) over 1999–2005 in China is 8.26 RMB ten thousand yuan per ton of SO_2, which is reasonably larger than that of CO_2 estimated in this paper. The forecasted MAC of CO_2 in this paper is similar to that estimated by

[3] The classification of light and heavy industry in Fig. 2 is the same as in Table 2. As Chenery et al. (1986) stated, the standard perception of industrialization is a general shift in relative importance from light to heavy industry. Light industry is usually of great importance at the early stage of industrialization and labor-intensive in nature with a relatively low ratio of capital to labor, while heavy industry is at the middle or late stage and capital-intensive with a relatively high ratio of capital to labor.

Table 2
The fitted and forecasted MAC (RMB yuan/ton of CO_2).

Sectors/industries	Fit period (1981–2010)					Forecasting period (2011–2020)	
	6–7th Five-Year Plan (1981–1990)	8th Five-Year Plan (1991–1995)	9th Five-Year Plan (1996–2000)	10th Five-Year Plan (2001–2005)	11th Five-Year Plan (2006–2010)	12th Five-Year Plan (2011–2015)	13th Five-Year Plan (2016–2020)
Coal	36	30	68	137	237	367	529
Petroleum Ext.	2	12	33	65	108	162	226
Ferrous Mi.	81	88	533	1309	2409	3832	5579
Non-Ferrous Mi.	72	132	623	1441	2585	4057	5856
Nonmetal Mi.	91	82	211	442	773	1205	1738
Wood Exp.	74	94	504	1206	2194	3468	5028
Food Proc.	55	20	115	364	733	1223	1833
Food Ma.	36	31	165	431	808	1297	1896
Beverage	27	47	149	318	553	854	1221
Tobacco	4	1	1	1	5	13	23
Textile	39	64	253	568	1010	1579	2275
Apparel	57	38	354	1005	1926	3117	4579
Leather	87	44	462	1340	2593	4223	6228
Wood Proc.	55	26	161	445	860	1405	2080
Furniture	210	70	746	2434	4879	8079	12,035
Paper	18	17	75	166	287	431	591
Printing	381	313	2199	5954	11,246	18,078	26,446
Cultural Articles	279	236	1817	5561	10,918	17,887	26,470
Petroleum Proc.	22	1	1	3	23	55	99
Chemical Products	9	10	24	50	90	147	222
Medicine	31	5	59	187	396	697	1100
Fibers	10	6	3	1	1	1	1
Rubber	35	23	165	491	961	1576	2336
Plastic	128	162	948	2352	4323	6861	9966
Nonmetal Ma.	23	14	44	100	180	282	406
Ferrous Press	11	17	22	28	35	42	51
Non-Ferrous Press	41	41	62	99	151	218	302
Metal Products	96	68	567	1492	2811	4523	6628
General Machinery	180	154	1006	2727	5171	8338	12,226
Special Machinery	61	132	505	1120	1977	3076	4418
Transport Equipment	38	98	362	792	1388	2148	3074
Electrical Equipment	191	74	830	2742	5500	9104	13,555
Computer	21	2	2	6	26	60	105
Measuring Instrument	466	209	2733	8806	17,527	28,895	42,911
Electric Power	2	1	1	1	1	1	3
Gas Prod.	7	20	29	37	44	50	56
Water Prod.	179	447	2218	5136	9163	14,301	20,549
Others	11	7	28	110	234	397	602
Light Industry	124	107	603	1816	3555	5821	8614
Heavy Industry	43	44	234	584	1080	1723	2512
Aggregated Industry	52	46	324	887	1689	2731	4012

Gao et al. (2004) using the MARKAL-MACRO model. They also found that the MAC of CO_2 in China is in fact considerably high; when the abating rate equals 45%, the MAC of CO_2 attains 250 USD/ton of CO_2.

As a theoretical measure, the estimated MAC in Table 2 is higher than the carbon tax rate that the enterprises are able to afford; however, it provides the benchmark of the market price when setting a carbon tax rate. Zhang and Baranzini (2004) denoted that the developed countries should levy a carbon tax in terms of the actual abating cost. The carbon tax currently levied in the developed countries is too low to stabilize the CO_2 concentration in the atmosphere; if the carbon tax is the only policy to abate CO_2, its rate should be higher. Barrett (1994) and Rauscher (1994) also stated that all governments have an incentive to distort the environmental tax downward from the Pigovian level in order to lower the costs of, and shift profits to, the home firm, which is sometimes referred to as ecological dumping. As opposed to other environmental policies, a carbon tax provides the pollution emitters with the economic incentive to change their behavior through a market mechanism. Thus, to fully reflect the institutional value of an environmental tax or a carbon tax, the carbon tax should be high enough to influence the emitters' behavior and the additional social cost must suffice to stimulate the emitters' consciousness of environmental protection.

In developing countries, levying a relatively lower carbon tax has its own rationality, which is beneficial to economic development and consistent with the common but differentiated abating principle advocated in the Kyoto Protocol. Reddy and Assenza (2009) have argued that the integration of climate policies with development priorities that are vitally important for developing countries and the need for using sustainable development as a framework for climate change policies should be stressed. Based on this, a lower carbon tax obviously favors economic development. As described previously, the carbon tax levied in the developed countries is also not high. For example, it's about 5.5–11.1 Euros/ton of CO_2 in Finland and Denmark and 37.9 Euros in Sweden. The MAC measured in Table 2 is in fact the hundred percent abating cost of CO_2 emissions that is impossible to attain in reality; therefore, in the following part of this paper, especially when forecasting the impact of carbon tax levy on the economy and the environment, the MAC of CO_2 emissions under the one percent abating scenario is specified as the appropriate CO_2 tax rate to be levied in China to satisfy the target of development priority. This is about 34 yuan per ton of CO_2 on average for the aggregated industry. The measures are similar to many other studies. For example, the estimated carbon tax rates are 39.2–399.3 RMB yuan/ton of CO_2 in He et al. (2002), 41.5–83.0 in Wei and Glomsrod (2002), 99–727 in Wang et al. (2005), 20–200 in Wang et al. (2009), and so on.

The CO_2 tax rate simulated in this paper is calculated in terms of the estimated MAC of CO_2 emissions reported in Table 2; thus, different from most of the existing studies, it will provide us with two particularly meaningful conclusions. The first is that the levied carbon tax rate should rise over time. Zhang and Baranzini (2004) obtained a similar conclusion based on a review of the literature. That is, the government should levy a continuously increasing carbon tax rate if it has to reflect the rising costs of damages from the accumulation of CO_2 concentration in the atmosphere, if it has to signal the markets that CO_2 emissions will eventually be heavily taxed, and if there are few economically feasible substitutes available. This signal strengthens the incentive for technical innovation needed to make more stringent future emissions targets affordable. Another conclusion is that the levied carbon tax should vary considerably across industrial sectors. As shown in Table 2, on average, the levied carbon tax in the light industry should be larger than in the heavy industry. For example, sectors with a carbon tax rate above 100 yuan per ton of CO_2 in the year 2015 mostly belong to the light industry, including Manufacturing of Furniture, Printing and Reproduction of Recording Media, Cultural Articles Manufacturing, General Machinery Manufacturing, Electrical Equipment Manufacturing, Measuring Instruments and Machinery, and Production and Supply of Water, the only one in the heavy industry. This is also consistent with the findings in many other studies. Hoel (1996) noted that, although an undifferentiated carbon tax should finally be levied according to standard welfare theory, this is not preferable in the short run due to the incomplete international climate agreement and the incentive for some countries to be a free rider. Therefore, all carbon emitters should not face the same carbon tax; for instance, carbon intensive tradable sectors should thus face a lower carbon tax than other sectors of the economy. Zhang and Baranzini (2004) also pointed out that there would be significant variation in the size of carbon taxes among countries and regions, given that the marginal cost of abating CO_2 emissions substantially differs across countries and regions.

Lee et al. (2007) argued that, since the implementation of a carbon tax is a complex problem that will most certainly not result in blanket reductions of CO_2 emission for all countries, it might well be that it should be implemented on a case-by-case basis involving at most a few countries from specific regions rather than as a one-for-all policy. Wang et al. (2005) also found that the MAC in the heavy industry, like electric power, coal, and petrochemical sectors, is lower, indicating that there is much room to abate CO_2 there. Though the carbon tax rate is relatively low in the heavy industry, the total amount of carbon tax is still larger than in the light industry due to its huge CO_2 emission.

The estimated MAC serves as a reference value not only for setting the environmental taxation rate but also for pricing the emission right trade. For example, one party is willing to purchase an emission permit that is lower than its own MAC to emit additional pollution, while another party shrinks its pollution by selling the permit at a price which is higher than its own MAC; the trade of permits continues until the MAC across countries, regions or sectors equalizes. In short, as opposed to administrative fiats and emission permit trade, environmental taxes, including carbon tax, are more flexible and endow firms with more choice. A firm can choose to emit and pay taxes or reduce emission and avoid the payment of carbon tax according to its own MAC of carbon emission. Therefore, environmental taxes make it possible for firms to react to market signals in an economic way and make a choice between the payment of taxes and the reduction of emission. The technological progress or innovation necessary for emission reduction will make additional profits; thus, firms always keep the motivation to further increase their ability to reduce emission.

5. Forecasting the impact of carbon taxation on the economy and the environment

Table 3 reports the out-of-sample one-period-ahead forecasting accuracy, the value of MAE, of two target variables by polynomials of Eq. (4) from the first to the fifth degree and the corresponding *p*-values of the Diebold–Mariano (DM) test for the MAE difference, which are defined as the significance levels at which the null hypothesis under investigation can be rejected. In calculating the DM statistic, the null hypothesis of equal forecasting ability is related to five benchmark models: linear, quadratic, cubic, quartic and quintic polynomials, referred to as DM1, DM2, DM3, DM4 and DM5, respectively. For instance, DM1 presents the test results for linear polynomial, where a *p*-value no greater than 0.05 indicates that the linear polynomial yields a higher forecasting error (in terms of absolute error) relative to the competing model at the 5% significance level, a *p*-value no smaller than 0.95 means that the linear polynomial produces a lower forecasting error at the 5% level, while a *p*-value between 0.05 and 0.95 implies that the benchmark and competing model have an equivalent forecasting accuracy from the viewpoint of statistics. The same interpretation applies to the *p*-values reported for DM2–DM5.

According to Table 3, for the target variable of industrial value-added, quadratic PDPDM produces the lowest value of MAE, but the quintic one yields the largest MAE. Can we obtain statistical evidence to support the quadratic PDPDM to be the best model when forecasting industrial value-added? The DM2 statistic (the quadratic polynomial is the benchmark model) shows that the forecasting ability of

Table 3
Comparison of forecasting error and choice of forecasting model.

Target variables	Model specification	MAE	DM1	DM2	DM3	DM4	DM5
Industrial value-added	Linear polynomial	170.63		0.9721	0.4933	0.0604	0.0000
	Quadratic polynomial	136.47	0.0279		0.0211	0.0000	0.0083
	Cubic polynomial	154.86	0.5067	0.9789		0.0385	0.0095
	Quartic polynomial	210.73	0.9396	1.0000	0.9615		0.0397
	Quintic polynomial	340.56	1.0000	0.9917	0.9905	0.9603	
CO_2 emission intensity	Linear polynomial	0.9362		0.0453	0.0286	0.0005	0.0398
	Quadratic polynomial	1.0469	0.9547		0.7922	0.0096	0.0261
	Cubic polynomial	1.0164	0.9714	0.2078		0.0097	0.0357
	Quartic polynomial	2.1574	0.9995	0.9904	0.9903		0.6154
	Quintic polynomial	1.6597	0.9602	0.9739	0.9643	0.3846	

the quadratic polynomial outperforms that of linear and cubic polynomials at the 5% significance level, and quartic and quintic ones at the 1% level. Other DM tests not only come to the same conclusion but also give us the result compared pairwise between any two models except the quadratic one. For instance, the linear polynomial is better than the quartic polynomial at the 10% significance level; linear and cubic polynomials have equal forecasting accuracy. Therefore, the quadratic PDPDM is chosen as the best model in this study to forecast the impact of the carbon tax variable on industrial value-added in the future. In a similar way, linear PDPDM is selected as the best model when forecasting the environmental variable of CO_2 emission intensity, which not only has the lowest forecasting error but is also supported statistically.

Table 4 presents the regression results of the policy variable (*PV*) on the two target variables based on the best forecasting model selected above. HT/IV estimation, the main method used in this study, shows that all the coefficients are statistically significant at least at the 5 percent level. As the secondary method, dynamic GMM estimation produces similar absolute values and signs to those of the HT/IV method for its coefficients estimators, which are also significant at least at the 5% level. Thus, the results estimated by the HT/IV method are robust enough and can be used to forecast the target variables in the future. *Wald* statistics reveal that the four models specified in this study are overall significant. General *F* tests show that there exists a heterogeneous effect across sectors and therefore the two-digit sectoral panel data analysis in this study, rather than aggregation analysis, is very necessary. As seen from Table 4, industrial value-added and CO_2 emission intensity have very high and significant values of positive autocorrelation coefficients (0.92–0.96), indicating that the lagged target variables contain plenty of historical information which will play an important role in forecasting the target variables. Obviously, the introduction of a dynamic explanatory variable is indispensable to the estimation and prediction of the economic and environmental variables in this study; such a conditional forecast based on all the historical information will have a relatively high forecasting accuracy. The coefficients of time trend variables are small but extremely significant – the industrial value-added of all sectors increases while CO_2 intensity decreases over time. Thus, the yeast effect exists in the Chinese industry in the sense that some common economy-wide factors tend to affect most sectors at the same time, rather than a limited number of sectors. Of course, the most important issue for this paper is the influence of *PV* on *TV*. As new information, the coefficients of *PV* are much less than the slopes of the historical information variable ($\ln TV$_lag1) and intercepts, but they are significant too. Due to the application of double-log models, the elasticity analysis is the most convenient here. For the model of CO_2 emission intensity, the slope of *PV* is just the elasticity value because the linear polynomial is utilized. A one percent increase of the carbon tax of *PV* significantly decreases CO_2 emission intensity by 0.0091–0.0096%, implying that the levy of a carbon tax will play an effective role in realizing the abatement goal of carbon intensity. Because the quadratic polynomial is chosen for the target variable of industrial value-added, the elasticity of *PV* is not straightforward and must be calculated in terms of $\partial(\ln TV_{it})/\partial(\ln PV_{it}) = \beta_1 + 2\beta_2 \ln PV_{it}$. According to the forecasted output elasticity of aggregated industrial carbon tax, during the period of the 12th Five-Year Plan, a 1%

Table 4
The effect of MAC on the economic and ecological variable: polynomial dynamic panel model (1980–2010).

$\ln TV$	Industrial value-added				CO_2 emission intensity			
	HT/IV		Dynamic GMM		HT/IV		Dynamic GMM	
	Coef.	*p*-Value	Coef.	*p*-Value	Coef.	*p*-Value	Coef.	*p*-Value
Constant	0.1906	0.000	0.2004	0.000	0.2704	0.006	0.1974	0.042
$\ln TV$_lag1	0.9547	0.000	0.9396	0.000	0.9506	0.001	0.9236	0.001
t	0.0092	0.002	0.0086	0.001	−0.0089	0.000	−0.0102	0.000
$\ln PV$	−0.0036	0.003	−0.0029	0.004	−0.0091	0.034	−0.0096	0.027
$\ln PV$ square	0.0010	0.027	0.0012	0.019				
Sectoral effect: general *F* test	676.47		591.94		384.56		475.21	
Overall significance: *Wald* test	90,084		67,141		97,001		62,369	

Note: The null hypothesis of least square restricted general *F* test for sectoral effect is $\beta_i = 0$ for all sectors.

rise of the carbon tax will decrease the industrial value-added by 0.0129%; then the value of elasticity becomes gradually smaller and decreases by only 0.0087% in 2020. The signs of the estimated coefficients in the quadratic polynomial of industrial value-added also tell us that, with the increase of the carbon tax rate, industrial value-added will first fall and then rise. It is thus evident that, in the short run, the levy of a carbon tax will increase the energy price, influence the input of energy factors, further increase the price of energy-intensive products and decrease their international competitiveness – leading to a negative impact on output. In the long run, the negative influence will disappear and carbon tax levy will promote output growth. However, even though a negative influence of carbon tax on output exists in the short run, its absolute value is of no consequence. The factor that plays the greatest role in forecasting industrial value-added is its historical information; the very high positive value of the autocorrelation coefficient proves that, as a whole, industrial value-added will still keep its strong growing trend regardless of the levy of a carbon tax.

Beginning with the estimated coefficients reported in Table 4, the recursive one-year-ahead forecasting values of industrial value-added and CO_2 emission intensity for 38 sectors over the forecasting interval of 2011–2020 are obtained. Fig. 2 depicts the sum of industrial value-added and averaged CO_2 intensity for light, heavy, and aggregated industry, respectively. Concretely, industrial value-added is the absolute value; thus, its area graphs for the light and heavy industry are drawn in panel (a), while CO_2 intensity is the relative indicator and its weighted averages are depicted in panel (b), in which the weights are just the actual and forecasted sectoral value-added behind panel (a).

Seen from panel (a) in Fig. 2, even under the scenarios of carbon tax levy, aggregated industrial value-added still increases from 16.7 thousand billion yuan of RMB in 2011 to 36.5 in 2020; its averaged growth rate is 8.14% annually, less than the historical averaged rate of 11.8% over 1980–2010. Though the output elasticity of the carbon tax is negative, its influence on output growth is very small; dominated more by its historical data, the growth rate of aggregated industrial value-added attains 7.9% per year in the period of the 12th Five-Year Plan, which is greater than the 6.9% forecasted in the 13th Five-Year Plan. Industrial value-added in the heavy industry is higher than that in the light industry; in 2011, the forecasted heavy industrial value-added is 12.3 thousand billion yuan while the light industrial one is just 4.4. In both light and heavy industry, output growth in the 12th Five-Year Plan is also higher than in the 13th Five-Year Plan. Until 2020, the forecasted heavy industrial value-added attains 28.8 thousand billion yuan, while the light industrial value-added attains 7.65. As shown in Table 2, the carbon tax rate levied in the light industry is higher than that in the heavy industry, but light industrial output is influenced less by the carbon tax due to its low total taxes; the heavy industry emits more than 95% of total industrial CO_2, leading to larger total carbon taxes although its tax rate is lower than that of the light industry.

Examine panel (b) of Fig. 2 again. Corresponding to the negative CO_2 intensity elasticity of carbon tax in Table 4, the aggregated industrial CO_2 emission intensity decreases with a big fluctuation from 34 tons of CO_2 per ten thousand yuan of industrial value-added in 1980 to 27.9 in 1995. It decreases more sharply and more smoothly in 1996–2010, and in 2010 falls to only 8.1 tons of CO_2 per ten thousand yuan, decreasing by 4.9% annually over the entire sample period. During the forecasting period, aggregated industrial CO_2 intensity still keeps a steadily decreasing trend from 7.99 ton of CO_2 per ten thousand yuan in 2011 to only 6.4 in 2020; it falls by an annual 2.4%, 2.15% in the 12th Five-Year Plan and 2.8% in the 13th Five-Year Plan. Relative to aggregated industrial CO_2 intensity in 2005 (11.2 tons/ten thousand yuan), under the scenarios of carbon tax levy in this study, it will have decreased by 42.7% in 2020, which is similar to the 40–45% abatement goal of CO_2 intensity officially announced by the Chinese central government, indicating that the levy of a carbon tax is beneficial to the successful realization of a binding abatement goal. As opposed to the heavy industry, the light industry has a much lower value of CO_2 intensity, leading to a relatively small influence of the light industry on weighted aggregated industrial CO_2 intensity even though its output weights are big; as shown in Fig. 2, the aggregated industrial CO_2 emission intensity is dominated by the heavy industry. In 1980–2010, the annual decreasing rate of CO_2 intensity in the light industry is 8.5%, quicker than the 4.4% in the heavy industry; in 2011–2020, due to the specified carbon tax levy, the annual decreasing rate of CO_2 intensity in the heavy industry is 2.78%, quicker than 0.97% in the light industry. Specifically, CO_2 intensity in the heavy industry decreases more rapidly in the period of the 13th Five-Year Plan than in the 12th Five-Year Plan, while CO_2 intensity in the light industry decreases more

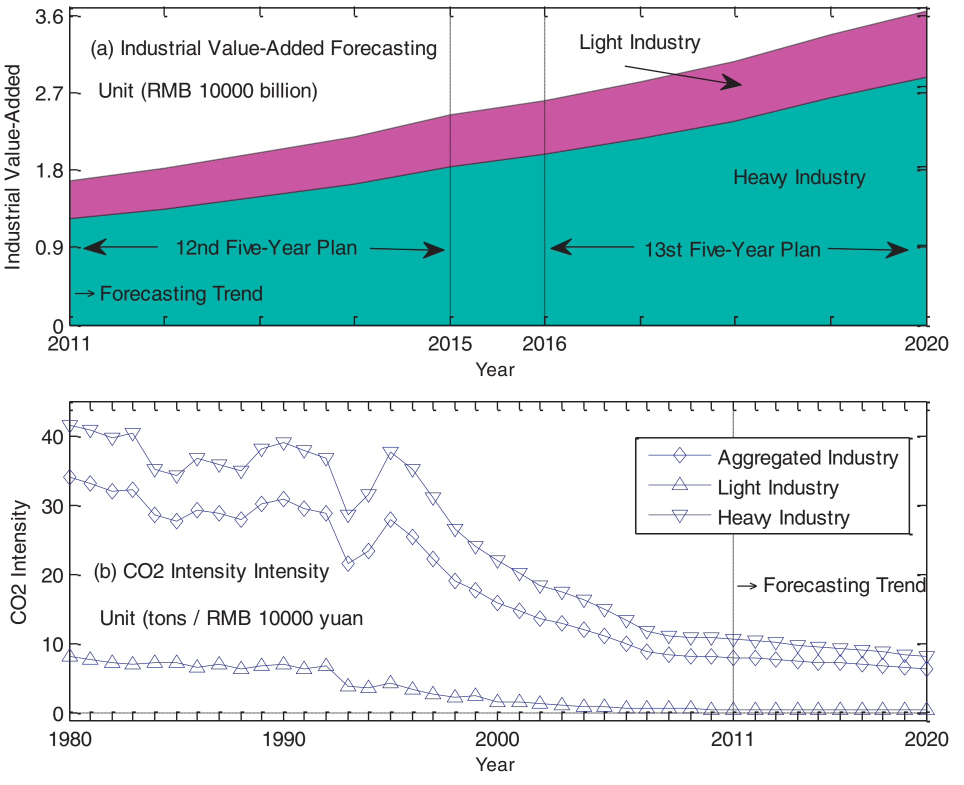

Fig. 2. One-year-ahead forecasting of value-added and CO_2 intensity under the scenario of carbon tax levy.

slowly in 2016–2020 than in 2011–2015. The forecasted values of CO_2 intensity for the light and heavy industry in 2020 are 0.49 and 8.07 tons of CO_2 per ten thousand yuan, which is a decrease by 45.08% and 46.25%, respectively, relative to the absolute value of 0.89 and 15 in 2005. In a word, the levy of a carbon tax plays an obvious role in abating industrial CO_2 intensity for either the emission-intensive heavy sector or the light industry with low emission. The scenarios of carbon tax levy specified in this paper lead to a reduction of CO_2 intensity corresponding to the official goal and are consistent with the requirement of development priorities in developing countries like China. Many studies have also found that a gradual abatement is preferable in the developing countries (Roughgarden and Schneider, 1999; Kuosmanen et al., 2009; Reddy and Assenza, 2009).

6. Conclusion

This paper estimates the marginal abatement cost of CO_2 emissions for industrial sectors over the reform period by using the directional distance function and utilizes it as the benchmark to calculate the carbon tax rate likely to be levied in the future. Forecasting based on the polynomial dynamic panel data model tells us that the levy of a carbon tax negatively influences the industrial value-added. However, the negative influence of a carbon tax on output is very small; driven more by the historical information, the aggregated industrial value-added still increases by 8.14% annually in the forecasting period, where its annual growth is 7.9% and 6.88% in the period of the 12th and 13th Five-Year Plan, respectively.[4] Though the carbon tax rate of the heavy industry is low, heavy industrial value-added is influenced more by the levy of a carbon tax than that of the light industry due to its huge

[4] Lin (2004) predicted that, by adapting technological know-how from advanced countries at a lower cost, China is very likely to maintain a GDP growth rate of around 8 percent for another twenty or thirty years.

total CO_2 emission. Carbon tax levy is obviously beneficial to the abatement of CO_2 emission intensity. The forecast reveals that the CO_2 intensity of the aggregated, light and heavy industry in 2020 will reduce by 42.7%, 45.08% and 46.25% relative to that in 2005, approaching the binding abatement goal of 40–45% announced by China at the end of 2009. In sum, the environmental effect of carbon tax levy is obvious because a carbon tax can promote CO_2 reduction in two ways: it can directly promote carbon intensity abatement by increasing the energy price, improving energy efficiency, etc., and indirectly by redistributing the carbon tax income, reinvesting in low carbon technology, adjusting the distortion of the traditional tax system, and so on. Therefore, based on the influential analysis of the impact of a carbon tax on the economy and the environment in this study, the gains from carbon tax levy outweigh its losses and the environmental taxation reform in China should begin with the levy of a carbon tax.

The design of a carbon tax in China may take the following points into account. The levy of a carbon tax is of urgency in China to challenge the climate change and achieve an agreement among countries to promissarily abate carbon after the expiration of the Kyoto Protocol in 2012. Low carbon investment, almost 40% of the RMB 4000bn recovery package in 2008, will reduce the shock of carbon tax levy in the beginning. The carbon tax should be levied from the production units that emit CO_2 directly into the atmosphere and be based on their total CO_2 emission. It is very convenient to levy a carbon tax in such a manner because the calculation of taxes is very simple due to fixed carbon emission coefficients of fossil fuels and electricity. It is also easier to urge firms to develop low carbon technology and make big efforts to abate carbon than to levy the carbon tax according to the carbon content of fossil fuels. The setting of the carbon tax rate could be based on the MAC of CO_2 emissions estimated in this study; it should increase over time and vary across industrial sectors.[5] As tested in this study, the levy of such a carbon tax will lead to a reduction of CO_2 intensity similar to the officially announced abatement goal, which satisfies China's development priorities. Of course, the levy of a carbon tax is only the first step of an environmental taxation reform in China. An environmental taxation reform is surely a systematic scheme and should be understood as the process from the second-best taxation system to the best one by continuously adjusting or removing the taxation distortion. Further studies on environmental taxation reform along this line will be left for the future.

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Appendix A

A.1. Creation of the sub-industrial panel database

This paper constructs an input and output panel database of the two-digital industrial sectors where the industrial sectors are classified according to the new version of the National Standard of Industrial Classification (GB/T4754), revised in 2002, in China. Data available for the period between 1980 and 2010 allow an analysis to be undertaken for 38 different industrial sectors which belong to three bigger categories: mining, manufacturing, electric power, gas and water production and supply. To this end, the sub-industries must be reclassified and recombined to match, the scope of all the industrial variables must be adjusted to the same statistical content, and some missing data must be added rationally. These constructed variables include gross output value of industry, industrial value-added, capital stock, labor force, energy consumption and carbon dioxide emission, of which the capital stock and CO_2 emission cannot be obtained directly and need estimating as explained below. All value-type variables are calculated based on the 1990 price level. The brief names of the 38 industrial sectors are listed in Tables 1 and 2.

[5] If calculated based on carbon rather than CO_2, the carbon tax rate can be obtained by multiplying the CO_2 tax rate measured in this study by 3.67.

A.1.1. The principle to create the sub-industrial database

In the course of creating the industrial sectoral databases, we face several problems. The first one is the inconsistency of data in the 1990s as compared to earlier data, especially from 1980 to 1984, due to different industrial classifications. We correct these data by re-classifying and re-combining them according to the correspondence relationship between old and new industrial classification criterions provided by the fourth appendix of the 1988 China Industry Economy Statistical Yearbook (page 373). The second issue is the inconsistency of the statistical scope. Before 1997, the sectoral data comes from industrial enterprises with independent accounting systems, including both urban industry and rural industry at the township level (xiang ji xiang yishang), while the sectoral data since 1998 includes state-owned and non-state-owned industrial enterprises only above the designated size. Non-state-owned industrial enterprises above the designated size are those with annual revenue from principal business over 5 million RMB. Fortunately, the China Statistical Yearbook also provides data of industrial sectors at the village level of rural industry (cun ban gong ye) before 1997 and the China Economic Census Yearbook reports the sub-industrial data of non-state-owned industrial enterprises with annual revenue from principal business below the designated size of 5 million RMB (guimo yixia) in 2004 and 2009. We add the former into the database before 1997 and use the latter to calculate the expanding proportion to adjust the data after 1998 in order to form input and output databases with the same statistical scope at the level of all industrial enterprises to achieve comparability of the data over the entire reform period.

A.1.2. Estimate on stock capital

The capital stock is estimated according to the underlying relationships behind the original and net value of fixed assets provided by the China Statistical Yearbook, following the steps below.

Step 1: Calculate the rate of depreciation δ for each sector over time using the expressions:

$$cd_t = ov\,fa_t - nv\,fa_t; \quad CD_t = cd_t - cd_{t-1}; \quad \delta_t = \frac{CD_t}{ov\,fa_{t-1}}$$

where *cd* is the value of cumulative depreciation, *ov fa* is the original value of fixed assets, *nv fa* is the net value of fixed assets and *CD* represents the current depreciation.

Step 2: Calculate the gross investment at the 1990 price using

$$inv_t = ov\,fa_t - ov\,fa_{t-1}; \quad I_t = \frac{inv_t}{P_{K,t}}$$

where *inv* is gross investment at the current price for each year, *I* is gross investment at the constant 1990 price depreciated according to the price indices of investment in fixed assets, P_K.

Step 3: Determine the original capital stock in the first year of 1980.

Set the net value of fixed assets in 1980 at the 1990 price level to be the original capital stock of the same year of 1980.

Step 4: Estimate the capital stock according to the perpetual inventory approach

$$K_t = I_t + (1 - \delta_t) \times K_{t-1}$$

A.1.3. Estimates on energy-induced carbon dioxide (CO_2) emissions

According to the World Bank definition, CO_2 emissions are those stemming from the burning of fossil fuels and the manufacture of cement, the former of which accounts for at least 70% of total CO_2 emission. Therefore, the CO_2 emission used is only related to fossil energy combustion; that is to say, CO_2 emission is computed from the consumption of primary solid coal, liquid oil, and gas fuels by using the following expression.

$$CO_2 = \sum_{i=1}^{3} CO_{2,i} = \sum_{i=1}^{3} E_i \times NCV_i \times CEF_i \times COF_i \times \left(\frac{44}{12}\right)$$

where CO_2 represents the flow of carbon dioxide with a unit of ten thousand tons, $i = 1, 2, 3$ correspond to three types of primary energy (coal, oil and gas), and E is their respective consumption. NCV is net calorific value provided by the China Energy Statistical Yearbook in 2007, CEF is the carbon emission factor provided by the guidebook of Intergovernmental Panel on Climate Change (IPCC) in 2006, and COF is the carbon oxidization factor set to be 1 for both oil and gas and 0.99 for coal in this study. Therefore, the calculated CO_2 emission coefficients for coal, oil and gas are 2.763, 2.145 and 1.642 tons of CO_2 per ton coal equivalent, respectively, in the case of China.

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