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Estimating the Marginal Abatement Cost Curve of CO₂ Emissions in China: Provincial Panel Data Analysis

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Estimating the Marginal Abatement Cost Curve of CO2 Emissions in China: Provincial Panel Data Analysis*

Limin DU, Aoife HANLEY and Chu WEI

Abstract

This paper estimates the Marginal Abatement Cost Curve (MACC) of CO2 emissions in China based on a provincial panel for the period of 2001-2010. The provincial marginal abatement cost (MAC) of CO2 emissions is estimated using a parameterized directional output distance function. Four types of model specifications are applied to fit the MAC-carbon intensity pairs. The optimal specification controlling for various covariates is identified econometrically. A scenario simulation of China's 40-45 percent carbon intensity reduction based on our MACC is illustrated. Our simulation results show that China would incur a 559-623 Yuan/ton (roughly 51-57 percent) increase in marginal abatement cost to achieve a corresponding 40-45 percent reduction in carbon intensity compared to its 2005 level.

Keywords: CO2 Emissions; Marginal Abatement Cost Curve; Model Selection; China

JEL: Q52, Q54, Q58

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1. Introduction

As the largest contributor of CO₂ emissions in the world, China has made a great effort to mitigate its rising trend of GHG emissions. In 2007, the authorities of the Central Government launched an energy-conservation and pollution-abatement program which aims to shift China towards being a low-carbon society. The authorities set a mandatory target for energy intensity (energy consumption per unit of GDP), Chemical Oxygen Demand (COD) and sulfur dioxide (SO₂)¹. To achieve this goal, each province is allocated its individual target of allowable emissions.

This goal is integrated into the national 11th Five-Year Plan (FYP) (2006-2010). According to the official figures, by the year 2010, the energy intensity, COD and SO₂ were already 19.1%, 12.45% and 14.29% lower, relative to the base year of 2005. In 2010, a new target to control the CO₂ intensity (CO₂ emissions per unit of GDP) was added to the 12th FYP. It is expected to be 17% lower in 2015 relative to the 2010 level.

Although the global community welcomes this China-led initiative to confront the problems associated with emissions, worries have been expressed on China's over-dependence on tough regulation rather than market-based criteria in achieving these objectives (Qiu, 2009; Zhang, 2011).

The World Bank has already evaluated China's 11th FYP and highlighted the usefulness of market-based criteria (World Bank, 2009). Other studies similarly suggest that flexible market-based instruments may help China to reach the emissions target with a lower abatement cost (Baumol and Oates, 1988; Wei et al., 2012). In a recent high-level political meeting, China's leaders pledged to let markets play a decisive role in the economy to make economic development more sustainable (Reuters, 2013)². Therefore, future exploration and identification of abatement opportunities in China will give higher consideration to solutions based on

¹ The mandatory reduction target for energy intensity is 20 percent by 2010 relative to 2005. The other two major pollutants, COD and SO₂ are both required to be reduced by 10 percent by 2010 relative to 2005 (The State Council, 2007).

² The third Plenary Session of the 18th Communist Party of China Central Committee

cost-effectiveness.

The Marginal Abatement Cost Curve (MACC) has recently attracted extensive attention and been increasingly applied in climate change policy. Its growing popularity is mainly due to its simplified representation of the complex relationship between emissions abatement effort and the marginal cost of cutting one unit of CO₂ emissions. For policy-makers, scholars and stakeholders in climate negotiation, MACC provides an illustrative guide to demonstrate the benefits of the emissions trading system. It helps to guide the estimation of permit prices and carbon taxes. It helps in the determination of a solution to achieve the most cost-effective emissions constraint target. Finally it helps in assessing the cost-effectiveness of various policy regimes (Ellerman and Decaux, 1998; Kesicki and Ekins, 2011; Klepper and Peterson, 2006).

The MACC has been widely used for global and country-specific scenario analyses. Researchers have investigated the MACC in some recent and related studies. However, provincial-level studies of this phenomenon are rare. Since China's government is a federal system and provinces are the major units responding to policy (Qian and Weingast, 1997), a province level MACC analysis can help to inform policy at a national level. In other words, it can assist the policy-makers to better identify the Marginal Abatement Cost (MAC) gap among regions and design a burden-sharing strategy. This paper attempts to fill this gap. We adopt a new strategy to develop a MACC for China's provinces by identifying the optimal modeling specification from among a set of competing specifications. The method which we use to estimate the MACC is one which is empirically tractable and easy to solve.

The main contribution of this paper is threefold. **First**, individual MACs for each province across the different years are estimated for a given production-based technology and then a MACC is estimated based on these individual MACs. **Second**, four types of commonly used MACC specifications are compared and the optimal one is chosen where the choice criteria are based on the model's in-sample and out-of-sample performance. **Third**, we apply this newly proposed MACC estimation

method to simulate the cost of China's carbon reductions for the year 2020, which has important policy implications for China's low carbon strategy.

The remainder of the paper is as follows. Section 2 will discuss previous studies and summarize the advantages and weaknesses of each approach. Section 3 presents four types of empirical specifications. Section 4 introduces the data and variables. The empirical results for all specifications are presented and compared in section 5. Section 6 simulates the economic cost for achieving China's carbon reduction target. The last section is the conclusion.

2. Literature Review

The previous research on MACC falls into three broad categories in terms of modeling approach (De Cara and Jayet, 2011; Kesicki and Strachan, 2011).

2.1 Expert-based MACC

The first category is the expert-based MACC, which is also called the *technology cost curve*. It is an engineering bottom-up approach that assesses the emissions reduction potential and corresponding cost of each single technical option based on assumptions developed by experts. Then the technical options are ranked from least to most expensive to represent the costs of achieving incremental levels of emissions reductions.

The earlier MACC serves as a supply curve. For instance, Jackson (1991) constructs a least-cost supply curve for GHG abatement and uses this methodology to evaluate the cost-effectiveness of 17 technical options. His analysis shows that the main determinants of cost savings are energy efficiency and whether it is a renewable energy source. The most well-known case is the global MACC developed by the McKinsey Company. In their latest version, they conduct an in-depth evaluation of the reduction potential and corresponding cost for more than 200 GHG abatement opportunities across 10 sectors and 21 countries/regions in 2030 (Nauclér and Enkvist, 2009). Expert-based MACC also can be applied to specific sectors. To investigate the

abatement potential in the agricultural sector, Moran et al. (2011) develop a MACC for crop and soil pollution in the UK by examining a range of specific abatement technologies/options in terms of their cost-effectiveness and mitigation potential.

Although it is easy to understand, the traditional expert-based MACC has also been heavily criticized (Kesicki and Strachan, 2011). Firstly, it treats each measure individually and neglects interactions between technical options and the associated co-benefit/co-cost. Secondly, it assesses only the technological cost and ignores the associated transaction cost. Thirdly, it only evaluates single-way impacts while neglecting the institutional and behavioral contexts. Finally, it works in a static way and neglects issues of inter-temporal dynamics and inertia.

In a recent study, Vogt-Schilb and Hallegatte (2011) attempt to improve the traditional expert-based MACC by incorporating a “cost in time” dimension. They argue that the more expensive options should be implemented before the potential of the cheapest ones has been exhausted if their potential is high and their inertia is significant. They suggest that policy-makers should consider these dynamic and inertia effects in determining the optimal implementation time of various GHG abatement measures.

2.2 Model-derived MACC

The second category is model-derived MACC. This specification integrates partial or general equilibrium models. For this branch of models, the most common way to generate a MAC curve is to run the model with different strict emission limits and to derive the corresponding CO₂ prices or to run the model with different CO₂ prices and calculate the corresponding CO₂ emission levels. Finally, researchers use the price-emission pairs to form a MAC curve.

The model-derived MACC can be further divided into two different types. One is engineering-oriented bottom-up models, such as the energy system model. Another is economy-oriented top-down models, such as Computable General Equilibrium (CGE) models (De Cara and Jayet, 2011; Klepper and Peterson, 2006). Both types of model

simulate the equilibrium by either minimizing the system costs or maximizing consumer and producer surplus. However, the bottom-up models are usually partial equilibrium models which only cover the energy sectors, while the top-down models are usually general equilibrium models which cover endogenous economic responses in the whole economy.

Ellerman and Decaux (1998) are the first to derive a global MACC by using MIT's *Emissions Prediction and Policy Analysis* (EPPA) model to measure the magnitude and distribution effects of the benefits from emissions trading. Criqui et al. (1999) carry out a similar study. They simulate various MACCs by applying the *Prospective Outlook on Long-term Energy Systems* (POLES) model and comparing two tradable emissions market specifications to meet the Kyoto Protocol's requirement. Springer (2003) screen 25 GHG permit trading models, comprising *Integrated Assessment Models* (IAM), CGE models and energy system models. The market volume and permit price for different market types are estimated using these models. Böhringer et al. (2009) construct a MACC using *Policy Analysis based on Computable Equilibrium* (PACE). Their numerical simulations confirm the existence of compliance costs which result from market segmentation and overlapping regulation. Using a *MARKAL-MACRO* model, Chen (2005) derives China's MACC for carbon emissions for 2010, 2020 and 2030. Their scenario simulation shows that, compared with the baseline year, China's marginal abatement cost is expected to reach 12-216 \$/t which corresponds to a reduction rate range from 5- 45%.

Klepper and Peterson (2006) exploit the *Dynamic Applied Regional Trade* (DART) model to simulate the mechanism path of how abatement level affects MACC through energy price. They found that the MACC is indeed determined by the initial energy price, the energy supply structure and the low-carbon potential. Morris et al. (2012) argue that the MAC is affected by policies abroad, i.e., the policies adopted in other third countries, the historic policy efforts and the coverage of tradable GHG. Fischer and Morgenstern (2006) adopt a meta-analysis strategy to explore the factors that contribute to the vast discrepancies in the MAC for different studies. They show that

several modeling assumptions may alter the estimates of MAC. For example, the Armington trade elasticity assumption may underestimate the MAC while the perfectly mobile capital assumption may upwardly bias the estimates.

Although model-derived MACCs have the advantage of taking into account interactions between mitigation measures and inter-temporal interactions, they also have disadvantages. Firstly, the estimated results of the system models diverge significantly. They are quite sensitive to the choice of the model used and the model's underlying assumptions. Secondly, system models are usually large complicated black boxes. Most of the time, readers are made aware of a particular result but have no understanding of how this results is obtained and whether the parameters used in the model are properly set.

2.3 Supply-side/Production-based MACC

The third approach bases on production theory to derive the MAC. The production possibility set is determined by a set of detailed technical and economic constraints. Given that the production process will generate both desirable output and undesirable by-products, the production unit has to sacrifice some profit by reallocating its productive resources to abatement activities to cut emissions at the margin. This constraint induced marginal cost can be interpreted as an opportunity cost (De Cara and Jayet, 2011; Klepper and Peterson, 2006).

There are two strategies to implement the empirical analysis. The first one is to specify a certain total cost function and then to obtain the marginal cost model by the first-order derivations, or to specify and estimate a marginal cost function directly. Related studies include Hartman et al. (1997) on the US, De Cara and Jayet (2011) on the EU, Dasgupta et al. (2001), Wei and Rose (2009) and Zhou et al. (2013) on China, etc.³ The main problem of this method is how to derive reliable cost information when such information is usually confidential.

Another major strand of the literature employs distance function frameworks to

³ See Zhou et al. (2014b) for a good review of the literature

model the environmental production technology. Both the Shephard distance function and the directional distance function have been widely used (Chung et al., 1997; Shephard et al., 1970). The main advantage of the distance function method is that it only requires data on inputs and outputs which are much easier to derive than cost information. Chambers et al. (1998), Färe et al. (1993) and Färe et al. (2005) have undertaken much pioneering work in this field.

Some empirical studies apply the non-parametric Data Envelopment Analysis (DEA) approach. DEA estimation is based on linear programming, and it aims to construct a piecewise linear combination of all observed inputs and outputs. Examples include Boyd et al. (2002), Kaneko et al. (2010), Lee et al. (2002), Maradan and Vassiliev (2005) and Choi et al. (2012) etc. The major advantage of the DEA approach is that it does not need to impose a specific functional form on the underlying technology (Zhang and Choi, 2014)⁴.

The shadow price also can be estimated parametrically. The main advantage of the parametric approach is that the estimated frontier is everywhere differentiable. In previous studies, the Shepard distance function is usually specified with a translog functional form while the directional distance function is commonly represented by a quadratic functional form. Both the Shepard/translog and the directional/quadratic setting can be estimated using the Linear Programming (LP) method. Related studies include Coggins and Swinton (1996), Marklund and Samakovlis (2007), Matsushita and Yamane (2012), Rezek and Campbell (2007), Swinton (2004), and Lee and Zhang (2012), etc. Moreover, the directional/quadratic setting can be estimated using the Stochastic Frontier Analysis (SFA) approach. Relevant previous studies include Färe et al. (2005), Murty et al. (2007) and Wei et al. (2013), etc. The advantage of the SFA relative to the LP method is that the former takes statistical noise into account⁵.

⁴ More detailed review of the DEA approach in energy and environment analysis can be found in Song et al. (2012), Zhang and Choi (2014) and Zhou et al. (2008).

⁵ Recently, increased efforts have been put into improving carbon performance modeling and shadow price estimation techniques. The first research strand uses non-radial directional distance functions to incorporate slacks into the efficiency measure (Barros et al., 2012; Färe and Grosskopf, 2010; Zhang and Choi, 2013b; Zhou et al., 2012). The second strand uses the meta-frontier technique to incorporate group heteroskedasticity into the analysis (Battese et al., 2004; Oh, 2010; Zhang et al., 2013). The third branch uses the bootstrapping method to provide

As most of the above studies reveal, discrete estimations of the MAC for different geographic spaces and time periods are not combined to form a continuous curve. This prevents researchers from being able to conduct a cost-benefit analysis using various abatement scenarios. This paper adopts the supply-side/production-based MACC strategy and aims to overcome its deficiencies. We first derive the MAC under the directional distance function framework by using panel data at the provincial level⁶. In the second step, various empirical specifications are used to fit our estimated MAC and the optimal parameterized MACC model will be identified according to different econometric selection criteria.

Compared to the expert-based MACC and the model-derived MACC, the supply-side/production-based MACC is solidly based in production theory and its interpretation is straightforward. It is also relatively transparent so that readers can easily appreciate the model in its entirety. Another attractive feature of our approach is that our estimations are based on provincial panel data, so that we are able to capture regional characteristics and a time trend. Moreover, we provide a series of functional forms for the MAC curve and choose the optimal one by using both in-sample fitting criteria and out-of-sample criteria, while previous studies usually only provide one option. Thus, our method has its own advantages. At least in some aspects, it represents an improvement to the approach used in previous studies.

3. Empirical Specifications

Assume the marginal CO₂ abatement cost curve is as follows:

$$y = f(x; Z) \tag{1}$$

where y is the marginal CO₂ abatement cost; x is the carbon intensity (CO₂/GDP),

estimation errors and confidence intervals for the non-parametric DEA and the parametric linear programming methods respectively (Simar and Wilson, 1999; Zhang and Choi, 2014; Zhou et al., 2010).

⁶ An anonymous reviewer has pointed out that it would be interesting for future research to conduct comparative studies on the MACC internationally e.g. to conduct a comparison among China, Korea, Japan and other East Asian countries. Such a comparison might provide more comprehensive policy implications (Zhang and Choi, 2013a).

Z is the vector of covariates, $f(\cdot)$ is the function relating these variables⁷.

It is worth noting that our definition of the marginal abatement cost curve differs from the traditional one since we do not use the absolute quantity of CO₂ abatement but rather we use carbon intensity on the right-hand side of Eq.(1). CO₂ emissions in China increased persistently during the time window but these increases are relative to China's economic growth for the period. Therefore, simply taking the levels of CO₂ emissions makes it difficult to pinpoint how much abatement is taking place. In order to capture the idea of CO₂ abatement more accurately, Zhou et al. (2013) calculate the amount of CO₂ emissions reduction by multiplying GDP for the current year by the change in carbon intensity between the current and previous year⁸. Following the latter, we deal with this problem in a more convenient way, i.e. by using carbon intensity to proxy for the quantity of emissions reduction and by investigating the relationship between marginal abatement cost and carbon intensity.

It is reasonable to use carbon intensity as a measure of the quantity of emissions reduction. First, the measure of marginal abatement cost which we use in this paper is highly related to GDP and CO₂ emissions (this will become clear in the next section). Second, adopting this carbon intensity proxy will not affect our resulting policy conclusions. In fact, using this carbon intensity measure aligns our analysis with those of policy-makers in China - the carbon reduction policies in China's 12th FYP (2011-2015) and other documents are mostly based on carbon intensity.

It is helpful to take a first look at the relationship between marginal abatement cost and carbon intensity by using a nonparametric method to begin with since the functional form is unknown. Specifically, we use the Locally Weighted Scatterplot Smoother (LOWESS) with a bandwidth of 0.8 and a tricube weighting function.

⁷ We are grateful to an anonymous reviewer for noting that our estimations capture the composite relationship of the shadow price and the other variables. Our analysis reports average effects, holding other things constant. We should note that access to more disaggregated sectoral information would open up interesting possibilities to researchers focusing on potential within-sector interactions among the covariates. Additionally, access to such data would allow researchers to relax the conventional assumption that the covariates exercise an equivalent impact across the different sectors.

⁸ Wei and Rose (2009) use the similar method when investigating the marginal cost curve of energy efficiency improvement.

[Figure 1 is here]

Figure 1 plots the LOWESS estimates of the relationship between marginal CO₂ abatement cost and carbon intensity. From Figure 1, we can observe an unambiguous nonlinear relationship between these two variables. The downward sloping curve means that it is more costly to reduce an additional unit of CO₂ emission for provinces in China with lower carbon intensities.

To estimate the relationship between the marginal CO₂ abatement cost and carbon intensity parametrically, we will consider four different functional forms for the function $f(\cdot)$, which are widely used by the previous studies, i.e. quadratic ($y = ax^2 + bx + c$), logarithmic ($y = a + b \ln x$), exponential ($y = e^{ax+b}$) and power ($y = ax^b$) functional forms (Chen, 2005; Criqui et al., 1999; Ellerman and Decaux, 1998; Morris et al., 2012; Nordhaus, 1991; Zhou et al., 2013). We will first estimate the MACC for all these four functional forms and then choose among these competing functional forms for the optimal specification.

4. Data and Descriptive Statistics

We use provincial level aggregate data that covers 30 provinces in China⁹. We constrain our analysis to the period of the 10th and 11th FYPs covering the years from 2001 to 2010 because policy was relatively stable during this period¹⁰.

The most important data needed for this paper is the MAC of CO₂ (denoted as *MAC*). Given that the cost data are unavailable, we have to estimate it ourselves. To do this, we resort to the method of shadow price estimation pioneered by Färe et al. (2005) which is based on the directional output distance function and multi-input multi-output production theory¹¹.

⁹ Tibet is excluded because of the problem of data availability.

¹⁰ Five Year Plans of China are economic and social development initiatives, which outline the directions, targets and methods of development. The 10th FYP covers the year 2001-2006 and the 11th FYP covers the year 2006-2010.

¹¹ It is worth noting that the estimation of the marginal abatement cost introduces further uncertainty pertaining to

The directional output distance function describes the simultaneous maximum expansion of good outputs and contraction of bad outputs that is feasible for any given production technology¹². Typically, the directional output distance function can be defined as:

$$\bar{D}_o(x, y, b; g_y, -g_b) = \max\{\beta : (y + \beta g_y, b - \beta g_b) \in P(x)\} \quad (2)$$

where $x = (x_1, \dots, x_N) \in \mathbf{R}_+^N$ is the vector of input, $y = (y_1, \dots, y_M) \in \mathbf{R}_+^M$ is the vector of good output, $b = (b_1, \dots, b_J) \in \mathbf{R}_+^J$ is the vector of bad output, and $g = (g_y, g_b) \in \mathbf{R}_+^M \times \mathbf{R}_+^J$ is the directional vector. The shadow price of the j -th bad output given the market price of the m -th good output is as follows:

$$q_j = -p_m \left[\frac{\partial \bar{D}_o(x, y, b; 1, -1) / \partial b_j}{\partial \bar{D}_o(x, y, b; 1, -1) / \partial y_m} \right], j = 1, \dots, J \quad (3)$$

Empirically, we employ the quadratic functional form to parameterize the directional output distance function. Additionally, we set the directional vector $(g_y, g_b) = (1, 1)$ to seek a simultaneous expansion of good output and reduction of bad output, a stylized fact arising from our reading of previous studies. The parameters of the quadratic function are estimated by the linear programming method (For more detailed description of the method, please refer to Appendix 1)¹³.

It is worth noting that the choice of different direction vectors will lead to different shadow price estimates. Given the direction of good output g_y , a larger value of bad

the accuracy of the estimates.

¹² The shadow price of the pollutant can also be estimated using the Shephard distance function. The difference is that the Shephard distance function expands the good and bad outputs proportionally, whereas the directional output distance function allows for a particular direction in which each output is to be expanded or contracted. The directional distance function is comparatively more flexible than the Shephard distance function. Indeed, the latter represents a special case of the directional distance function (Chung, et al., 1997). Moreover, Vardanyan and Noh (2006) find that the quadratic-based directional output distance function is more appropriate for application in shadow-pricing studies than the translog-based Shephard output distance function due to its mapping flexibility.

¹³ The directional output distance function also can be estimated parametrically using the Stochastic Frontier Analysis (SFA) method. The advantage of SFA is that it takes statistical noise into account. However, the SFA method cannot incorporate constraints into the estimation. Previous studies proceed by initially running the SFA estimation and ignoring the constraints. Researchers subsequently examine whether the results meet the constraints ex-post, only retaining for further analysis those results meeting the constraints (Färe, et al., 2005; Murty, et al., 2007). However, the exclusion of some observations may introduce inconsistency into the estimated parameters because these parameters have been estimated using the overall sample. As a result, the estimated shadow prices may be biased.

output direction g_b will lead to a higher estimated shadow price (Vardanyan and Noh, 2006; Zhou et al., 2014a).

In order to estimate the provincial shadow price of CO₂ reduction, we consider the case of one good output, annual regional Gross Domestic Product, one bad output, carbon dioxide emissions, and three inputs, labor, capital and energy. The data for GDP is deflated to the 2005 price to net out the effect of inflation. Labor input is measured as the number of employed persons at the end of each year. The data for GDP and labor inputs are both obtained from the China Statistical Yearbooks. Energy consumption is measured in the standard coal equivalent, which is collected from the provincial statistical yearbooks.

The data for capital stock is not directly available from any of the statistical yearbooks. Thus, we estimate it by the following perpetual inventory method as Zhang et al. (2004) have proposed:

$$K_{i,t} = K_{i,t-1}(1 - \rho_i) + I_{i,t} \quad (4)$$

where $I_{i,t}$ and $K_{i,t}$ are gross investment and capital stock for province i in year t respectively; $K_{i,t-1}$ is the capital stock of province i in year $t-1$; and ρ_i is the depreciation rate of capital stock for province i . The annual investment data is derived from the China Statistical Yearbooks. As before, we depreciate it to the 2005 price.

Similarly, we need to estimate the bad output, provincial CO₂ emissions. Following IPCC (2006) and Du et al. (2012), we estimate CO₂ emissions from the burning of fossil fuels by the following formula:

$$CO_2 = \sum_{i=1}^6 E_i \times CF_i \times CC_i \times COF_i \times (44/12) \quad (5)$$

where i represents an index of different types of fossil fuels. We consider the consumption of 7 different primary fuel types, i.e. coal, coke, gasoline, kerosene, diesel, fuel oil and natural gas. The term 44/12 is the ratio of the mass of one carbon

atom when combined with two oxygen atoms to the mass of an oxygen atom. The variables E_i , CF_i , CC_i and COF_i represent the total consumption, the relevant transformation factor, the carbon content and the carbon oxidation factor of fuel i , respectively. The data for provincial fuel consumption is taken from the regional energy balance tables in the China Energy Statistical Yearbooks.

It is interesting to briefly examine the estimated shadow prices.¹⁴ Figure 2 plots the kernel density curves of the shadow prices for four selected years. From the figure, we can observe that the kernel density curves shift rightward over time, indicating an increasing trend in shadow prices. In 2001, the shadow prices deviate from about 500 Yuan/ton to 1600 Yuan/ton with the majority of the estimates clustering around the 1000 Yuan/ton mark. The kernel density curve shifts significantly to the right by 2010, exhibiting a wider dispersion range and a lower clustering point. The shadow prices deviate from about 900 Yuan/ton to about 5800 Yuan/ton with most of the estimates now clustering around the 1700 Yuan/ton mark by 2010¹⁵.

[Figure 2 is here]

Once the estimates for CO₂ emissions are derived, then the provincial carbon intensities (denoted as *Cintens*) can be calculated. Furthermore, in the regression model, we consider the following covariates to control the provincial characteristics¹⁶.

Composition of Energy Consumption (denoted as *ratio_coal*). The relative CO₂ emissions of fossil fuels vary considerably. Specific CO₂ emissions from coal burning are 1.6 times that from natural gas and 1.2 times that from oil (Zhang, 2000). To control for potential provincial varying trends in fuel mix, we use the share of coal usage in total energy consumption to proxy for the composition of energy

¹⁴ If the readers are interested in more detailed shadow price estimates, please contact the authors.

¹⁵ The MAC estimates itself can be applied to emission allowance allocation. Zhou et al. (2014a) show how emission allowance can be allocated to different provinces and periods with efficiency as a criterion based on several centralized DEA models. Zhou et al. (2015) further argue that grandfathering allocation plan of initial emission allowances may benefit the heavy industries while hurt the light industries. They suggest that the MACs of the participants should be used as a supplementary criterion in the initial allocation of the allowance in order to establish a fair carbon market.

¹⁶ For our regressions, we used economic theory and previous research to inform our choice of control variables. Thus, we are reasonably confident that omitted variable bias is not a major issue in our analysis. Adding further control variables can certainly reduce the risk of omitting variables and generally reduce the variance as well. However, we have to achieve a good balance between the need for accuracy and parsimony.

consumption. The data on coal and total energy consumption is derived from the China Energy Statistical Yearbooks.

Industrial Composition (denoted as *ratio_heavy*). Usually heavy industry is more energy intensive than light industry and consequently produces more CO₂ emissions. Thus, it is helpful to control for the potential variation in the composition of industry among provinces over time. We measure industrial composition by the share of heavy industry over total industry for each province in terms of the value of gross output. The required data is taken from the statistic yearbooks of each province over the relevant years.

Urban Concentration (denoted as *ratio_urban*). The relationship between urban concentration and its effect on energy consumption and CO₂ emissions has been investigated in several studies (Karathodorou et al., 2010; Shim et al., 2006). Thus, it is appropriate to control for the variations of provincial urbanization level over time. We use the proportion of the non-agriculture population to the total population to proxy for the level of urbanization. All data is derived from the China Population Statistics Yearbooks and the China Population and Employment Statistics Yearbooks.

Privately-Owned Vehicles (denoted as *private_car*). China has experienced a tremendous growth in motor vehicles during the past decade. Until the late 1990s, automobiles in China were mainly owned by state-owned enterprises and government officials, but recently the number of privately-owned cars has grown rapidly (Auffhammer and Carson, 2008). The CO₂ emissions from motor vehicles have already had a detrimental impact in China (Riley, 2002). Thus we include privately-owned vehicles in our regressions, as measured by the number of privately-owned vehicles per 10 thousand persons. The data for privately-owned vehicles is derived from the China's Auto Market Almanac.

[Table 1 is here]

Table 1 lists the descriptive statistics for the variables¹⁷. From the table, we can

¹⁷ Our estimated CO₂ abatement shadow price exceeds the prices reported for six pilot carbon transaction markets in China. Though the market price represents an appropriate benchmark for estimations involving shadow prices,

observe that there are substantial variations over provinces and across years.¹⁸

5. Empirical Results

In this section, we will present the regression models and report the estimation results for the four different types of functional form. To search for the optimal specification, we estimate 6 step-wise regressions for each functional form by including different covariates. Then, we use both in-sample fitness criteria and out-of-sample forecasting criteria to choose the optimal regression model.

The in-sample criteria used are Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The out-of-sample criteria used are the Root Mean Squared Forecast Error (RMSFE) and the Mean Absolute Error (MAE). The in-sample fitness criteria are more suitable for in-sample predictions since their calculations are based on the in-sample fitness of the regressions, while for the out-of-sample forecasting, RMSFE and MAE are preferred (the calculation formulas of AIC, BIC, RMSFE and MAE are described in Appendix 2). Smaller values for the AIC and BIC, as well as RMSFE and MAE, are preferred.

5.1 Quadratic Functional Form

For the quadratic MACC estimation, we consider the following two-way panel regression model¹⁹:

we should also note that they are not identical. The shadow price reflects the opportunity cost, whereas the market price is heavily determined by the supply and demand of permits. Accordingly, the market price does not necessarily reflect all the abatement costs (Smith, et al., 1998; Wei, et al., 2013). Indeed, Vardanyan and Noh (2006) similarly find that no single estimation technology produces outcomes that are consistently close to the market prices of allowances.

¹⁸ Matsushita and Yamane (2012) use almost the same methodology to estimate the shadow price of CO₂ emissions in Japan and obtain a much lower value than ours. Possible reasons for this discrepancy are as follows. First, Matsushita and Yamane (2012) confine their analysis to Japan's power sector while we focus on China's overall economy. China's power sector is recognized as the main CO₂ emissions emitter (especially coal-fuelled plants). Thus, it is relatively cheap for the power sector to reduce CO₂ emissions compared to other sectors (e.g. services sector). We consider all sectors (i.e. agriculture sector, financial sector and education sector, etc), almost all of which are less carbon intensive than the power sector implying that it becomes more expensive for these sectors to cut CO₂ emissions. In this context, our higher estimated average shadow price is plausible. Secondly, this results discrepancy may be due to the use of different estimation techniques. Though both papers employ a quadratic directional functional form, there are slight differences. In our paper, we add both province and time dummies to capture the effects of provincial idiosyncratic effects and technology change while Matsushita and Yamane (2012) only consider time effects.

¹⁹ We are grateful to an anonymous reviewer for pointing out that our model is not focused on intertemporal aspects, i.e. the influence from previous years or expectations about future years.

$$y_{it} = \alpha + \beta x_{it}^2 + \gamma x_{it} + \phi Z_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (6)$$

where y_{it} is the shadow price of province i in year t ; x_{it} is the carbon intensity; Z_{it} is the vector of covariates; μ_i is the provincial specific characteristics; λ_t is the time effect; and ε_{it} is the error term. As mentioned before, we estimate 6 step-wise regressions. Then, we search for the optimal regression by applying in-sample and out-of-sample criteria.

We test the group-wise heteroskedasticity for all six regressions by using the modified Wald statistic (Greene, 2000). The null hypothesis of this test is that there is no group-wise heteroskedasticity. At the same time, we implement the Wooldridge test for serial correlation in panel data models for all the six regressions (Wooldridge, 2002). The null hypothesis of the Wooldridge assumes that there is no serial correlation. The test results show that the null hypotheses for both tests for all of the six regressions are overwhelmingly rejected. To handle the problems of heteroskedasticity and serial correlation, we resort to the method of Feasible Generalized Least Squares (FGLS) for panel data models, with the assumption of heteroskedasticity error with no cross-sectional correlation and panel specific AR(1) autocorrelation within panels. The results of the FGLS estimations for the six regressions are reported in Table 2.

[Table 2 is here]

Model 1 includes only carbon intensity and its quadratic term as independent variables. The estimation results show that both coefficients are significant at the 1 percentage level. The coefficient for the quadratic term is positive, indicating that the shape of the estimated MACC should be U-shaped (quadratic).

Model 2-5 controls for industrial composition, the structure of energy consumption, urban concentration, and privately-owned vehicles. Model 6 furthermore includes the time trend in its logarithmic form in line with Auffhammer and Carson (2008) to control for possible technology change. The estimation results show a relatively stable

relationship between the marginal CO₂ abatement cost and the carbon intensity. All regressions report negative coefficients for the carbon intensity and positive coefficients for its quadratic term. They are all significant to the 1 percentage level. Additionally, the coefficients of carbon intensity as well as its quadratic term in Model 2-6 are very close to those coefficients obtained in Model 1.

The last four rows reported in Table 2 are in-sample information and out-of-sample information criteria. Both the AIC and BIC criteria show that Model 6 is the optimal specification in the sense of its in-sample fitness. However, Model 5 is the optimal one when we judge based on out-of-sample forecasting criteria since both the MAE and RMSFE for Model 5 outperform the corresponding values in the other regressions. Because the coefficient of the time trend in Model 6 is insignificant even at the 10 percent level, we therefore consider Model 5 to be the optimal specification for the quadratic MACC estimation.

Once the optimal regression model is determined and the coefficients are estimated, it is easy to calculate the axis of symmetry of the parabola to be about 6 ton/10000 Yuan. Accordingly, the overall average for carbon intensity in China during the sample period is about 2.88 ton/10000 Yuan and none of the yearly average carbon intensity exceeds 3.2 ton/10000 Yuan. This means that the marginal CO₂ abatement cost curve relates to the downward part (left-side) of the U-shaped curve.

[Figure 3 is here]

Figure 3 simulates the estimated quadratic functional form MACC with the covariates set at their average values. We can see from the figure that for values of carbon intensity lying below 6 tons/10000 Yuan, the marginal CO₂ abatement cost will rise increasingly rapidly with decreasing carbon intensity.

5.2 Logarithmic Functional Form

Consider the following two-way logarithmic functional form MACC regression model:

$$y_{it} = \alpha + \beta \ln(x_{it}) + \phi Z_{it} + \lambda_i + \mu_i + \varepsilon_{it} \quad (7)$$

where the variables are defined as in Eq.(6). The difference is that carbon intensity in Eq.(7) is expressed in logarithmic form and its quadratic term is excluded from the regression.

Similarly, we test the group-wise heteroskedasticity and autocorrelation for all the six regressions by using the modified Wald statistic and Wooldridge test respectively. The results show that all six regressions suffer from problems of heteroskedasticity and autocorrelation. As before, we resort to using the method of FGLS for panel data, with the assumption of heteroskedasticity error with no cross-sectional correlations and panel specific AR(1) autocorrelation within panels. Table 3 reports the estimation results.

[Table 3 is here]

As before, Model 1 simply investigates the relationship between marginal CO₂ abatement cost and carbon intensity without controlling for any of the other factors. The estimation results show that the coefficient of carbon intensity is significant at the 1 percent level. The coefficient is negative, indicating that the marginal CO₂ abatement cost curve has a downward slope.

Similarly, Model 2-6 furthermore includes industrial composition, the composition of energy structure, urban concentration, privately-owned vehicles and a time trend. The estimation results show that the coefficients of carbon intensity in all these regressions are significantly negative. The results are stable and very similar as well as being similar to the results obtained in Model 1.

The results for the AIC and BIC show that Model 6 is the optimal specification in the sense of in-sample fitness. However, Model 5 is the optimal specification according to the out-of-sample forecasting criteria, MAE and RMSFE. Since the time trend is seen to be insignificant, we consider Model 5 as the optimal specification for the logarithmic functional form MACC estimation.

[Figure 4 is here]

Figure 4 simulates the marginal CO₂ abatement cost curve adopting the logarithmic functional form. From the figure, we can observe that the curve is downward sloping and convex, which means that China has to sacrifice proportionately more to reduce an additional unit of CO₂ emission as carbon intensity further decreases.

5.3 Exponential Functional Form

To estimate this exponential functional form ($y = e^{ax+b}$), we need to take the logarithm on both sides first, and then include the covariates and error term. Thus, we have the following two-way exponential functional form MACC regression model:

$$\ln(y_{it}) = \alpha + \beta x_{it} + \phi Z_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (8)$$

Note that the shadow price in the regression is now expressed in its logarithmic form while the carbon intensity is expressed as a level. The other variables are similar to Eq.(6) and Eq.(7).

Again, we test the group-wise heteroskedasticity and autocorrelation for all six regressions by implementing the modified Wald test and Wooldridge test respectively. Our results indicate that all six regressions experience problems of heteroskedasticity and autocorrelation. Thus, we employ the method of FGLS once again, assuming that the structure of the error term within groups is heteroskedastic and there is panel specific within-group AR(1) autocorrelation. Table 4 reports the estimation results.

[Table 4 is here]

The estimation results listed in Table 4 show that, regardless of whether we control or not for additional covariates, the coefficients of carbon intensity are negative and significant at the 1 percent level, indicating that the MACC is a downward sloping curve. Compared with the previous two functional forms, the results are similar except for the coefficient of the time trend. The information criteria show that regression 5 is the best one in the sense of its in-sample fitness. However, regression 6 performs best in terms of its out-of-sample forecasting ability. We

therefore choose regression 6 as the optimal model for the exponential functional form MACC estimation since our investigation is aimed at providing a basic tool for future policy analysis.

[Figure 5 is here]

Figure 5 simulates the exponential functional form MACC with the covariates set at their average values. From the figure, we can again observe that the marginal abatement cost will increase with the decline in carbon intensity. The curve is convex, though this convexity is not as pronounced as the previous two functional forms.

5.4 Power Functional Form

For the power functional form ($y = ax^b$), we need to take the logarithm on both sides. Then, we can construct the following two-way panel regression model:

$$\ln(y_{it}) = \alpha + \beta \ln(x_{it}) + \phi Z_{it} + \lambda_i + \mu_i + \varepsilon_{it} \quad (9)$$

We can see that both the shadow price and carbon intensity in the regression model are now expressed in the logarithmic form. The covariates are as used before.

Likewise, the modified Wald test and Wooldridge test are implemented, and the results show significant evidence of group-wise heteroskedasticity and autocorrelation for all six regressions. To avoid these problems, we run the FGLS, assuming that the structure of the error term is heteroskedastic without cross-sectional correlations as well as auto-correlated with panel specific AR(1) specification. Table 5 reports the estimation results.

[Table 5 is here]

From Table 5, we find that the coefficients of carbon intensity are negative and significant at 1 percent level, indicating a downward sloping curve. On average, a 1 percent decrease in carbon intensity will induce a 0.245-0.397 percent increase in the shadow price, ceteris paribus. The coefficient of the time trend in regression 6 is not significant even at the 10 percent level. The AIC and BIC show that regression 5 is the optimal one from the view of its in-sample fitness, while the MAE and RMSFE

reveal that regression 6 is the best in terms of its out-of-sample forecasting ability. We choose regression 5 as the optimal specification since the time trend coefficient is insignificant.

[Figure 6 is here]

Figure 6 plots the simulated power functional form MACC. From the figure, we find that the MACC clearly represents a downward sloping convex curve. This means that the marginal abatement cost increases more rapidly with additional decreases in carbon intensity.

To choose the optimal functional form, we can resort to the in-sample fitness criteria and out-of-sample forecasting criteria as well. From our estimation results, we can observe that the quadratic and logarithmic functional forms perform much better than the exponential and power functional forms since both the in-sample and out-of-sample criteria of the former two functional forms are much lower. The choice between the quadratic form and the logarithmic form is not so clear cut, but it is still possible for us to make an unambiguous choice. Although the BIC of the logarithmic form is lower, the other three criteria of this functional form, i.e. AIC, MAE and RMSFE, are higher. Thus, we are inclined to take the quadratic functional form as the optimal one. Moreover, the quadratic functional form is more flexible than the logarithmic functional form. Thus, we suggest to choose the quadratic functional form for policy analysis.

6. Simulation the Cost of China's Carbon Reduction

Having estimated the $MACC^{20}$, we are able to conduct some policy analysis. One obvious place to start for policy is to estimate the economic cost of achieving the Chinese government declared CO_2 reduction goal - i.e. to reduce the carbon intensity

²⁰ Strictly speaking, the national MAC for each year should be firstly estimated and then a national MACC can be econometrically derived. However, this procedure requires a considerable stretch of time-series data. Given our short period (2001-2010), we use the convention of taking the panel dataset of provincial MACs derive a weighted national MACC. The national MACC accordingly is comprised of the average of provincial MACCs, assuming that all parameters of the provincial MACCs are the same.

by 40-45 percent by the year 2020, compared with 2005 levels. We simulate the cost of CO₂ reduction based on the quadratic MACC since it is the optimal functional form.

To focus on the relationship between the marginal abatement cost and carbon intensity, the covariates in 2020 should be predetermined. We consider three scenarios according to the setting of covariates, including Business As Usual (BAU) scenario, Fast Development (FD) scenario and Slow Development (SD) scenario. Table 6 reports the details of the scenario setting.

[Table 6 is here]

The share of heavy industry. He et al. (2009) and Du et al. (2012) argue that the share of heavy industry in China will decline gradually with further economic development and rising environmental awareness. However, for 2006-2010, the share of heavy industry remained virtually unchanged. Thus, we assume that, for the BAU scenario, it will decrease 0.5% for both periods of 2011-2015 and 2016-2020. For the FD scenario, we assume that it will decrease 0.5% for the period 2011-2015 and decrease 1% per year for the period 2016-2020. For the LD scenario, we assume that it will maintain the 2010 level for 2011-2015 and decrease 0.5% per year for the period 2016-2020.

The share of coal consumption. The 12th FYP for Energy Development (2011-2015) declares that the government aims to reduce the share of coal consumption by about 3 percentage points. Under pressure to undertake further cuts in carbon emissions, it is reasonable to assume that the share of coal consumption in China will decline further over the period 2016-2020. We assume that, for the BAU scenario, it will decrease 3% for 2011-2015 and will decrease a further 5% for the period 2016-2020. For the FD scenario, we assume that it will decrease 5% for both the 2011-2015 and 2016-2020 periods respectively. For the LD scenario, we assume that it will decrease by 3% for both the 2011-2015 and the 2016-2020 periods.

The level of urbanization. According to the 12th FYP (2011-2015), the

urbanization ratio of China will increase by about 4% for the period 2011-2015. Considering that the urbanization level increased by 7 percentage during the period 2001-2010 and the government stresses the importance of urbanization for China's economic development during the next ten years, we have good reasons to expect a continuing trend of increased urban concentration for the next decade. We assume that, for the BAU scenario, it will increase 4% for both the 2011-2015 and the 2016-2020 periods. For the FD scenario, we assume that it will increase 5% both the 2011-2015 and the 2016-2020 periods. For the LD scenario, we assume that it will increase 4% for 2011-2015 and increase 3% over the duration of the 2016-2020 periods.

The private-owned car ownership. Huo and Wang (2012) forecast that the growth rate in private vehicle ownership in China amounts to an annual rate of about 14% from 2010 to 2020. The possession of vehicles per 10000 persons increased from 74 in 2001 to 468 in 2010, with an annual growth rate of roughly 20 percent. However, some large cities, such as Beijing, Shanghai and Hangzhou, have already begun to limit the growth of private vehicles due to traffic congestion problems. Thus, we assume that, for the BAU scenario, that private vehicle ownership will grow at an annual rate of 15% for the period 2011-2015 and 10% for the period 2016-2020. For the FD scenario, we assume that it will increase by 15% per year for the period 2011-2020. For the LD scenario, we assume that it will increase by 10% for the period 2011-2020.

Carbon intensity in 2005 corresponded to about 3.1 tons per 10000 Yuan of GDP and the corresponding marginal CO₂ abatement cost amounted to about 1099 Yuan. If the carbon intensity in 2020 decreases by 40-45 percent, it will amount to a decrease of 1.71-1.86 tons per 10000 Yuan of GDP in 2020.

[Table 7 is here]

Table 7 reports the simulation results of cost changes for the three scenarios. From the table, we can observe that for a 40-45 percent CO₂ reduction, China has to face a dramatic increase in marginal abatement cost. For the BAU scenario specification, the marginal CO₂ abatement cost will increase to 1673 Yuan if the reduction target is 40

percent and increase to 1702 Yuan if the reduction target is 45 percent, which correspond to increases of 52 percent and 55 percent respectively compared to the 2005 level. Our results from the FD scenario and LD scenario are very close to those from the BAU scenario²¹.

7. Conclusion

This paper tries to estimate the MACC of CO₂ emissions in China. In a first step, we estimate the individual marginal abatement cost of CO₂ emissions at the provincial level. The directional output distance function combined with panel data covering 30 provinces for the period 2001-2010 are used. In a second step, the provincial MAC-CO₂ intensity pairs are used to form a MACC. Four types of MACC specifications are econometrically estimated and the optimal one is chosen in accordance with in-sample and out-of-sample criteria. Moreover, the estimated MACC is applied to simulate the scenario of China's CO₂ intensity pledge.

The regression results show that the share of heavy industry, the level of urbanization and private car ownership rates are strongly positively correlated with the marginal abatement cost of CO₂ emissions, while the share of coal consumption imposes a significant negative effect. The magnitude of each coefficient should be interpreted in line with the different function form. Taking the exponential form as an example, if the share of heavy industry increases by 1 percentage point, the shadow price will increase by 0.387 percent. Similarly, a 1 percentage point increase in the coal share will lead to a 0.446 percent decrease in the shadow price.

The estimated MACCs are downward sloping and convex when specified in logarithmic, exponential and power functional forms. It means that China has to incur increasingly high costs in the process of cutting down its CO₂ intensity and achieving the ambitious 40-45 percent target as promised. In the U-shaped quadratic case, the

²¹ To provide more detailed policy implications of the MACC, we need to simulate the cap-and-trade system or the carbon tax. In view of the scope of our current paper, we do not include these additional topics. However, they would represent interesting and important topics for future research efforts.

turning point of carbon intensity is around 6 tons/10000 Yuan. For the provinces having CO₂ intensities in excess of the turning point²², it means that CO₂ abatement activities are beneficial since the marginal cost will decrease with the decrease in carbon intensity. However, for other provinces with carbon intensity lower than the turning point, it will become more expensive to control an additional unit of emissions since the MAC will increase more rapidly with successive cuts in CO₂ intensity.

The simulation of cost changes due to carbon intensity reduction shows that, the Chinese government has to bear a 51-57 percent increase in marginal abatement cost for achieving a 40-45 percent reduction in carbon intensity compared with its 2005 level. Fortunately, the decline of carbon intensity (or low-carbonization) does not only necessitate an economic cost. The improvement of environmental quality and social welfare is normally treated as a social benefit although it is hard to measure this benefit in money terms.

Our results have important implications for different stakeholders and MACC users. **For empirical researchers**, this production-based approach provides, in some aspects, a better alternative way to estimate the MACC. Our approach offers sufficient flexibility that relevant environment variables can be integrated. Additionally, it is relatively transparent and easy to apply. At least, the estimation via a production-based approach can be used as a benchmark or comparison when different approaches are adopted.

For policy-makers, this MACC offers a strong tool and is sufficiently informative to guide policy design and implementation. It can be used to simulate the cost consequences of various reduction exercises e.g. the cap-and-trade system and the carbon tax policy etc. Then, policy-makers can choose an optimal option from among the different affordable options, such as how to set a feasible carbon reduction target, how to allocate the initial permits for the cap-and-trade market and how to decide the carbon tax rate, etc. Relative to carbon tax, the Chinese government is more interested

²² There are four provinces with carbon intensity higher than 6 ton/10000 Yuan in specific years: Shanxi (2001-2005), Inner Mongolia (2004,2006), Guizhou (2001,2003-2007), Ningxia (2003-2010)

in carbon emissions trading systems. Actually, China has already launched seven regional pilot carbon emissions trading schemes in Shenzhen, Shanghai, Beijing, Guangdong, Tianjin, Chongqing and Hubei. For the next step, the Chinese government aims to build a nation-wide carbon emission trading market to improve the efficiency and fairness of carbon reductions.

It is worth noting that our method proposed in this paper is heavily relied on the estimated MACs, and the choices of direction vector, functional form and estimation technology may affect the final results. Thus it is important to refine the estimation method of MACs for the future research. Additionally, the assumptions of simulation scenarios may affect the results of carbon abatement cost projection. Thus it is important to adjust the scenarios from time to time for policy analysis according to the actual situation. Moreover, we have only simulated the abatement cost change for the year 2020 while the carbon emissions trading market are not involved. For the future researches, it is interesting to simulate the cost and welfare results of emissions trading market in China since the Chinese government is planning to establish a nation-wide carbon emissions trading market.

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Appendix 1: Estimation of Shadow Price

The shadow price of a pollutant can be estimated within the framework of multi-input multi-output production technology which considers pollutants as byproducts.

Suppose that a producer employs a vector of inputs $x = (x_1, \dots, x_N) \in \mathbf{R}_+^N$ to produce a vector of good outputs $y = (y_1, \dots, y_M) \in \mathbf{R}_+^M$ and a vector of bad outputs $b = (b_1, \dots, b_J) \in \mathbf{R}_+^J$. The production technology can be defined as the following output set:

$$P(x) = \{(y, b) : x \text{ can produce } (y, b)\} \quad (\text{A.1})$$

The directional output distance function describes the simultaneous maximum expansion of good outputs and contraction of bad outputs that is feasible for any given production technology. Formally, the directional output distance function is defined as

$$\bar{D}_o(x, y, b; g_y, -g_b) = \max\{\beta : (y + \beta g_y, b - \beta g_b) \in P(x)\} \quad (\text{A.2})$$

where $g = (g_y, g_b) \in \mathbf{R}_+^M \times \mathbf{R}_+^J$ is a directional vector which specifies the direction of the output vector.

The directional output distance function satisfies the translation property:

$$\bar{D}_o(x, y + \alpha g_y, b - \alpha g_b; g_y, -g_b) = \bar{D}_o(x, y, b; g_y, -g_b) - \alpha \quad (\text{A.3})$$

where α is a scalar. This property says that if the desirable output is expanded by αg_y and the undesirable output is contracted by αg_b simultaneously, the resulting value of the directional output distance function will be reduced by α .

By evoking the duality between the directional output distance function and the revenue function, Färe et al. (2005) is able to derive the shadow price of the j -th bad output given that the market price of the m -th good output is known.

$$q_j = -P_m \left[\frac{\partial \bar{D}_o(x, y, b; 1, -1) / \partial b_j}{\partial \bar{D}_o(x, y, b; 1, -1) / \partial y_m} \right], j = 1, \dots, J \quad (\text{A.4})$$

To estimate the shadow price, we employ the quadratic functional form to parameterize the directional output distance function and set the directional vector $(g_y, g_b) = (1, 1)$ to seek a simultaneous expansion of good output and reduction of bad output (Chambers et al., 1998; Färe et al., 2005; Färe et al., 2006; Murty et al., 2007).

We consider the case of three inputs, one good output and one bad output. Assume that there are $k=1, \dots, K$ provinces producing in $t=1, \dots, T$ years. Then, the quadratic directional output distance function for province k in year t can be represented as

$$\begin{aligned} \bar{D}_o(x_k^t, y_k^t, b_k^t; 1, -1) = & \alpha + \sum_{n=1}^3 \alpha_n x_{nk}^t + \beta_1 y_k^t + \gamma_1 b_k^t + \frac{1}{2} \sum_{n=1}^3 \sum_{n'=1}^3 \alpha_{nn'} x_{nk}^t x_{n'k}^t \\ & + \frac{1}{2} \beta_2 (y_k^t)^2 + \frac{1}{2} \gamma_2 (b_k^t)^2 + \sum_{n=1}^3 \eta_n x_{nk}^t b_k^t + \sum_{n=1}^3 \delta_n x_{nk}^t y_k^t + \mu y_k^t b_k^t \end{aligned} \quad (\text{A.5})$$

To capture the province and time effect, we add a set of province dummy variables and time dummy variables in the intercept term as Färe et al. (2006) have done:

$$a = a_0 + \sum_{k=1}^{K-1} \lambda_k S_k + \sum_{t=1}^{T-1} \tau_t T_t \quad (\text{A.6})$$

where λ_k and τ_t are the coefficients of the dummy variables. The province dummy variable $S_{k'} = 1$ if $k' = k$ and 0 otherwise. Similarly, the time dummy variable $\tau_{t'} = 1$ if $t' = t$ and 0 otherwise²³.

To estimate the parameters of the quadratic function, a deterministic linear programming algorithm is employed which is proposed by Aigner and Chu (1968). This approach minimizes the sum of the deviations of the estimated directional output distance functions from that of the frontier, having the advantage of allowing us to

²³ An alternative method to model regional heterogeneity is to use meta-frontier analysis. A typical meta-frontier analysis can be implemented in two steps. The first step is to classify the provinces into different groups according to their characteristics (such as location, wealth or industrial structure etc.) and to estimate the group-specific production frontier for each group respectively. The second step is to estimate the meta-frontier as the envelopment of the group-specific frontiers. For a more detailed description on the concept and estimation procedure, please refer to Battese et al. (2004), Chiu et al. (2012), Oh (2010) and Zhang et al. (2013).

impose parametric restrictions on the quadratic functional form.

$$\begin{aligned}
& \min \sum_{t=1}^T \sum_{k=1}^K (\bar{D}_o(x_k^t, y_k^t, b_k^t; 1, -1) - 0) \\
& s.t. \text{ (i) } \bar{D}_o(x_k^t, y_k^t, b_k^t; 1, -1) \geq 0, k = 1, \dots, K; t = 1, \dots, T \\
& \text{ (ii) } \bar{D}_o(x_k^t, y_k^t, 0; 1, -1) < 0, k = 1, \dots, K; t = 1, \dots, T \\
& \text{ (iii) } \frac{\partial \bar{D}_o(x_k^t, y_k^t, b_k^t; 1, -1)}{\partial b} \geq 0, k = 1, \dots, K; t = 1, \dots, T \\
& \text{ (iv) } \frac{\partial \bar{D}_o(x_k^t, y_k^t, b_k^t; 1, -1)}{\partial y} \leq 0, k = 1, \dots, K; t = 1, \dots, T \\
& \text{ (v) } \frac{\partial \bar{D}_o(\bar{x}, y_k^t, b_k^t; 1, -1)}{\partial x_n} \geq 0, n = 1, 2, 3; k = 1, \dots, K; t = 1, \dots, T \\
& \text{ (vi) } \beta_1 - \gamma_1 = -1, \beta_2 = \gamma_2 = \mu, \delta_n - \eta_n = 0, \quad n = 1, 2, 3 \\
& \text{ (vii) } \alpha_{n,n'} = \alpha_{n',n}, \quad n, n' = 1, 2, 3
\end{aligned} \tag{A.7}$$

The first set of restrictions (i) ensures that all observations are feasible, which implies that each observation is located either on or below the boundary. Restrictions in (ii) impose the null-jointness property, which means that, for $y > 0$, the output bundle $(y, 0)$ is not technically feasible. Restrictions in (iii) and (iv) are monotonicity assumptions in bad and good outputs respectively, which ensures the correct sign of the calculated shadow prices. Restrictions in (v) impose positive monotonicity constraints on the inputs for the mean level of input usage, which means that, at the mean level of inputs, an increase in input usage holding good and bad outputs constant causes the directional output distance function to increase. The parameter restrictions given by (vi) impose translation property. Additionally, the symmetry restrictions are imposed in (vii).

Once the parameters of the directional output distance function have been estimated, we are able to calculate the shadow price of the bad output for each province in each year. The shadow price of the bad output can be written as

$$q = -p \frac{\gamma_1 + \gamma_2 b + \sum_{n=1}^3 \eta_n x_n + \mu y}{\beta_1 + \beta_2 y + \sum_{n=1}^3 \delta_n x_n + \mu b} \tag{A.8}$$

Appendix 2: Calculation of AIC, BIC, RMSFE and MAE

The calculation formulas for AIC, BIC, RMSFE and MAE in this paper are mainly based on Auffhammer and Steinhauser (2012).

The AIC and BIC are calculated as follows respectively:

$$AIC = \ln\left(\sum_i \sum_t \frac{e_{it}^2}{n}\right) + \frac{2k}{n} \quad (\text{A.9})$$

and

$$BIC = \ln\left(\sum_i \sum_t \frac{e_{it}^2}{n}\right) + \frac{k}{n} \ln(n) \quad (\text{A.10})$$

where k is the number of coefficients, n is the number of observations, e_{it} is the error term for province i in year t .

The main idea of out-of-sample criteria is that, for a sample of N individuals and $n+m$ observations for each individual, using the first n observations to estimate the parameters and save the last m observations for forecasting. Let $\hat{f}_{i,n+h}$ be the one-step-ahead forecast of the true value $y_{i,n+h+1}$ for $i=1,2,\dots,N$ and $h=0,1,\dots,m-1$. The forecast errors are the difference of true value and forecasted value $\hat{e}_{i,n+h+1} = y_{i,n+h+1} - \hat{f}_{i,n+h}$, and each individual has m forecast errors.

The Root Mean Squared Forecast Error (RMSFE) is the sample standard deviation of the forecast errors that defined as follows:

$$RMSFE = \left(\frac{1}{mN} \sum_{i=1}^N \sum_{h=0}^{m-1} \hat{e}_{i,n+h+1}^2\right)^{1/2} \quad (\text{A.11})$$

The second common measure is the Mean Absolute Error (MAE), which is the average of the absolute forecast errors:

$$MAE = \frac{1}{mN} \sum_{i=1}^N \sum_{h=0}^{m-1} |\hat{e}_{i,n+h+1}| \quad (\text{A.12})$$

It's preferred to choose the model with the smallest value of RMFSE and MAE. In

this paper, we use the first 5 years' observations for the estimation of the coefficients and save the last 5 years' observations for the calculation of RMFSE and MAE.

Tables

Table 1: Descriptive Statistics

Variables	description	Units		Mean	Std. Dev.	Min	Max
<i>MAC</i>	Marginal abatement cost	10000 Yuan	Overall	0.13	0.07	0.01	0.58
			Between		0.05	0.06	0.24
			Within		0.05	0.00	0.47
<i>Cintens</i>	Carbon intensity	Ton/10000 Yuan	Overall	2.88	1.63	0.73	8.52
			Between		1.60	1.09	7.42
			Within		0.41	0.17	4.24
<i>Ratio_heavy</i>	Share of heavy industry	%	Overall	0.73	0.11	0.40	0.95
			Between		0.10	0.53	0.93
			Within		0.05	0.51	0.86
<i>Ratio_coal</i>	Share of coal consumption	%	Overall	0.77	0.13	0.30	0.94
			Between		0.13	0.36	0.93
			Within		0.03	0.68	0.89
<i>Ratio_urban</i>	Urban concentration	%	Overall	0.35	0.16	0.15	0.89
			Between		0.16	0.16	0.83
			Within		0.03	0.19	0.43
<i>Private_car</i>	Privately owned vehicles	Vehicles/10000 persons	Overall	228.24	250.20	19.15	1894.25
			Between		198.64	77.25	1137.99
			Within		155.98	-458.50	984.50

Table 2: Estimates of Quadratic MACC

Dependent variable: <i>MAC</i>	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
<i>Cintens* Cintens</i>	0.002 ^{***} (0.000)	0.003 ^{***} (0.000)	0.003 ^{***} (0.000)	0.002 ^{***} (0.000)	0.002 ^{***} (0.000)	0.002 ^{***} (0.000)
<i>Cintens</i>	-0.027 ^{***} (0.003)	-0.037 ^{***} (0.004)	-0.031 ^{***} (0.004)	-0.027 ^{***} (0.004)	-0.028 ^{***} (0.004)	-0.025 ^{***} (0.004)
<i>Ratio_heavy</i>		0.150 ^{***} (0.014)	0.132 ^{***} (0.014)	0.054 ^{***} (0.012)	0.082 ^{***} (0.016)	0.068 ^{***} (0.018)
<i>Ratio_coal</i>			-0.065 ^{***} (0.015)	-0.012 (0.014)	-0.035 ^{**} (0.017)	-0.046 ^{***} (0.017)
<i>Ratio_urban</i>				0.055 ^{***} (0.014)	0.050 ^{***} (0.016)	0.052 ^{***} (0.018)
Ln(<i>private_car</i>)					0.011 ^{***} (0.001)	0.011 ^{***} (0.002)
Ln(<i>time</i>)						0.002 (0.002)
<i>constant</i>	0.166 ^{***} (0.006)	0.082 ^{***} (0.008)	0.135 ^{***} (0.016)	0.114 ^{***} (0.013)	0.077 ^{***} (0.017)	0.088 ^{***} (0.018)
Estimation Method	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS
AIC	-5.497	-5.645	-5.651	-5.626	-5.898	-5.915
BIC	-5.460	-5.595	-5.589	-5.552	-5.811	-5.816
MAE	0.078	0.066	0.067	0.067	0.051	0.058
RMSFE	0.012	0.010	0.010	0.010	0.008	0.008

Notes: 1) standard errors in parentheses.

2) ^{***}, ^{**} and ^{*} represent significant at 1%, 5% and 10% levels respectively.

Table 3: Estimates of Logarithmic MACC

Dependent variable: <i>MAC</i>	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
<i>Ln(Cintens)</i>	-0.037*** (0.003)	-0.042*** (0.004)	-0.038*** (0.005)	-0.030*** (0.004)	-0.038*** (0.005)	-0.032*** (0.005)
<i>Ratio_heavy</i>		0.098*** (0.014)	0.097*** (0.014)	0.044*** (0.011)	0.086*** (0.015)	0.065*** (0.017)
<i>Ratio_coal</i>			-0.040*** (0.015)	-0.002 (0.012)	-0.035** (0.017)	-0.041** (0.017)
<i>Ratio_urban</i>				0.073*** (0.015)	0.049*** (0.015)	0.058*** (0.018)
<i>Ln(private_car)</i>					0.010*** (0.001)	0.011*** (0.002)
<i>Ln(time)</i>						0.003 (0.002)
<i>constant</i>	0.149*** (0.004)	0.079*** (0.008)	0.109*** (0.015)	0.083*** (0.012)	0.056*** (0.017)	0.067*** (0.018)
Estimation Method	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS
AIC	-5.523	-5.565	-5.589	-5.650	-5.890	-5.924
BIC	-5.499	-5.528	-5.539	-5.588	-5.816	-5.838
MAE	0.079	0.068	0.069	0.065	0.058	0.056
RMSFE	0.013	0.010	0.011	0.009	0.008	0.008

Note: 1) standard errors in parentheses.

2) ***, ** and * represent significant at 1%, 5% and 10% levels respectively.

Table 4: Estimates of Exponential MACC

Dependent variable: ln_MAC	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
<i>Carboninten</i>	-0.062 ^{***} (0.006)	-0.094 ^{***} (0.008)	-0.076 ^{***} (0.009)	-0.049 ^{***} (0.008)	-0.050 ^{***} (0.013)	-0.056 ^{***} (0.012)
<i>Ratio_heavy</i>		0.766 ^{***} (0.092)	0.602 ^{***} (0.092)	0.136 (0.091)	0.470 ^{***} (0.128)	0.387 ^{***} (0.133)
<i>Ratio_coal</i>			-0.253 ^{***} (0.121)	-0.403 ^{***} (0.092)	-0.516 ^{***} (0.138)	-0.446 ^{***} (0.144)
<i>Ratio_urban</i>				1.236 ^{***} (0.104)	0.915 ^{***} (0.108)	0.796 ^{***} (0.111)
Ln(<i>private_car</i>)					0.086 ^{***} (0.012)	0.078 ^{***} (0.015)
Ln(<i>time</i>)						0.035 ^{**} (0.016)
<i>constant</i>	-2.128 ^{***} (0.017)	-2.533 ^{***} (0.062)	-2.296 ^{***} (0.109)	-2.362 ^{***} (0.092)	-2.693 ^{***} (0.140)	-2.564 ^{***} (0.154)
Estimation method	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS
AIC	-1.377	-1.506	-1.491	-1.730	-1.942	-1.889
BIC	-1.352	-1.469	-1.442	-1.668	-1.868	-1.802
MAE	0.528	0.466	0.476	0.472	0.379	0.361
RMSFE	0.408	0.339	0.368	0.326	0.238	0.224

Note: 1) standard errors in parentheses.

2) ^{***}, ^{**} and ^{*} represent significant at 1%, 5% and 10% levels respectively.

Table 5: Estimates of Power MACC

Dependent variable: \ln_MAC	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$\ln(Cintens)$	-0.273 ^{***} (0.024)	-0.397 ^{***} (0.029)	-0.296 ^{***} (0.033)	-0.245 ^{***} (0.026)	-0.266 ^{***} (0.042)	-0.268 ^{***} (0.042)
<i>Ratio_heavy</i>		1.146 ^{***} (0.102)	0.838 ^{***} (0.105)	0.238 ^{***} (0.092)	0.623 ^{***} (0.131)	0.560 ^{***} (0.142)
<i>Ratio_coal</i>			-0.163 ^{***} (0.142)	-0.218 ^{**} (0.092)	-0.360 ^{**} (0.143)	-0.330 ^{**} (0.148)
<i>Ratio_urban</i>				1.170 ^{***} (0.097)	0.831 ^{***} (0.108)	0.669 ^{***} (0.111)
$\ln(private_car)$					0.084 ^{**} (0.012)	0.084 ^{**} (0.014)
$\ln(time)$						0.024 (0.016)
<i>constant</i>	-2.002 ^{***} (0.028)	-2.686 ^{***} (0.068)	-2.489 ^{***} (0.128)	-2.489 ^{***} (0.093)	-2.793 ^{***} (0.143)	-2.663 ^{***} (0.158)
Estimation method	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS
AIC	-1.485	-1.636	-1.552	-1.713	-1.951	-1.894
BIC	-1.460	-1.599	-1.502	-1.651	-1.876	-1.807
MAE	0.525	0.442	0.447	0.470	0.375	0.352
RMSFE	0.398	0.306	0.330	0.320	0.232	0.215

Note: 1) standard errors in parentheses.

2) ^{***}, ^{**} and ^{*} represent significant at 1%, 5% and 10% levels respectively.

Table 6: Scenario Setting

Scenarios	Scenario descriptions
Business As Usual scenario	<ul style="list-style-type: none">• The share of heavy industry: decreases 0.5% per year for 2011-2015, and decreases 0.5% per year for 2016-2020.• The share of coal consumption: decreases 3% for 2011-2015 and decreases further 5% for 2016-2020.• The urbanization ratio: increases 4% for 2011-2015 and increases 4% for 2016-2020.• Private-owned car ownership: increases 15% per year for 2011-2015 and increases 10% per year for 2016-2020.
Fast Development scenario	<ul style="list-style-type: none">• The share of heavy industry: decreases 0.5% per year for 2011-2015 and decreases 1% per year for 2016-2020.• The share of coal consumption: decreases 5% for 2011-2015 and decreases further 5% for 2016-2020.• The urbanization ratio: increases 5% for 2011-2015 and increases 5% for 2016-2020.• Private-owned car ownership: increases 15% per year for 2011-2015 and increases 15% per year for 2016-2020.
Slow Development scenario	<ul style="list-style-type: none">• The share of heavy industry: maintains 2010 level for 2011-2015 and decreases 0.5% per year for 2016-2020.• The share of coal consumption: decreases 3% for 2011-2015 and decreases further 3% for 2016-2020.• The urbanization ratio: increases 4% for 2011-2015 and increases 3% for 2016-2020.• Private-owned car ownership: increases 10% per year for 2011-2020.

Table 7: Simulated MAC of CO₂ Reduction in China

	Marginal abatement cost (Yuan)			Growth rate compared to 2005 level		
	BAU	FD	LD	BAU	FD	LD
40%	1673	1693	1658	52%	54%	51%
45%	1702	1722	1687	55%	57%	54%

Note: the average provincial marginal abatement cost is 1099 Yuan in 2005.

Figures

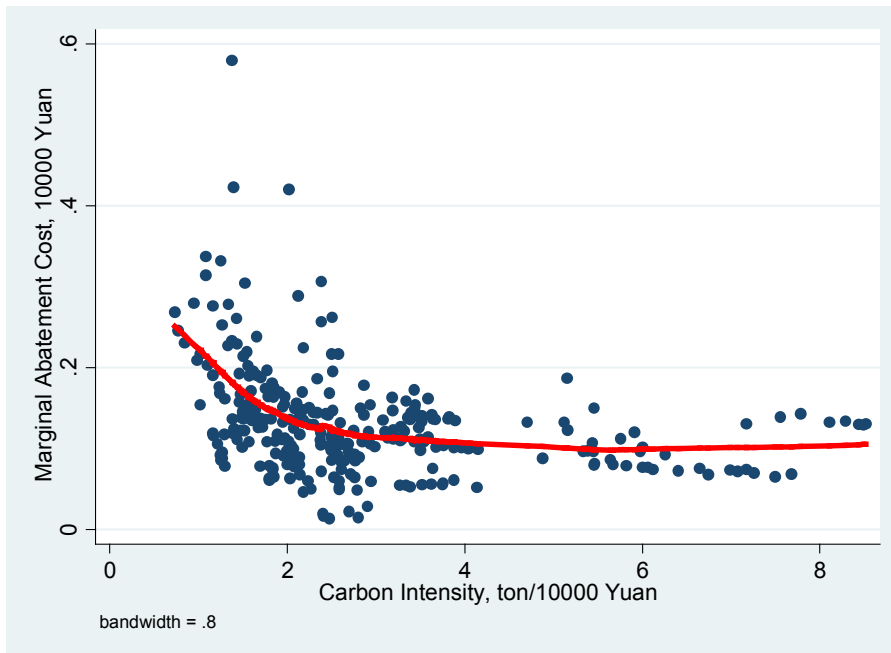


Figure 1: LOWESS Smoother

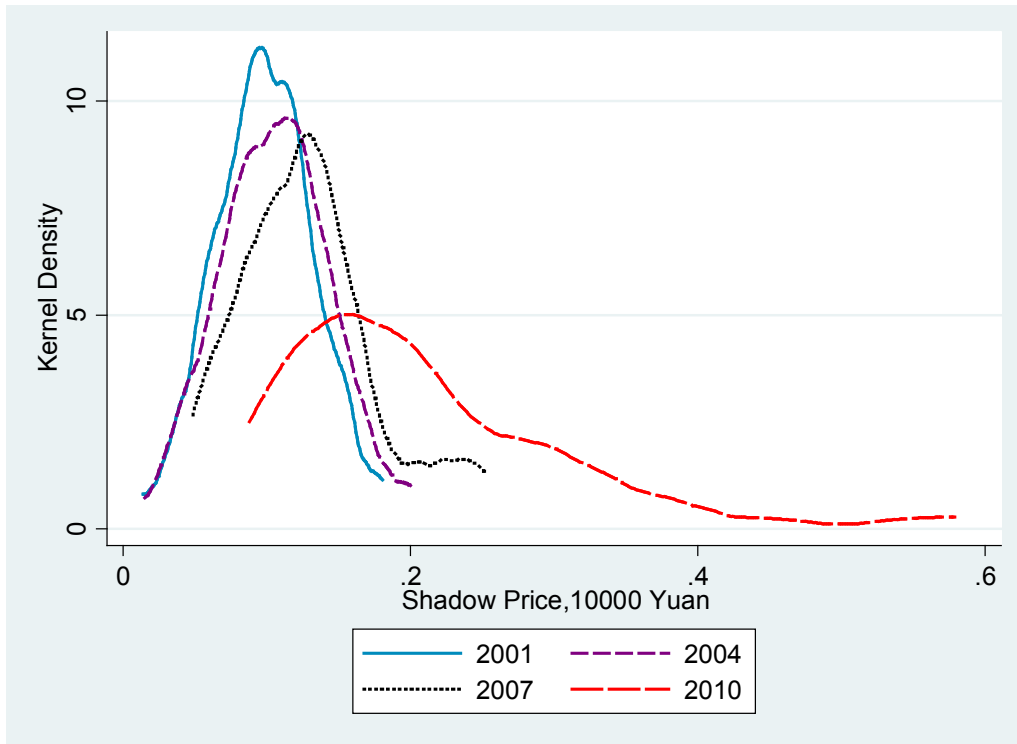


Figure 2. Kernel Density of the Shadow Price Estimates

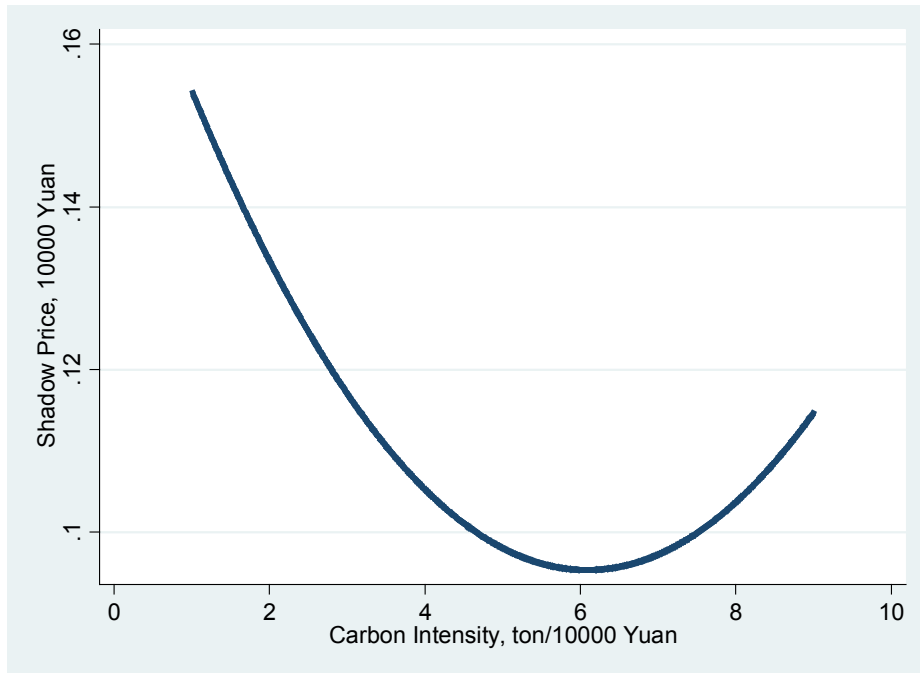


Figure 3: MACC in Quadratic Functional Form

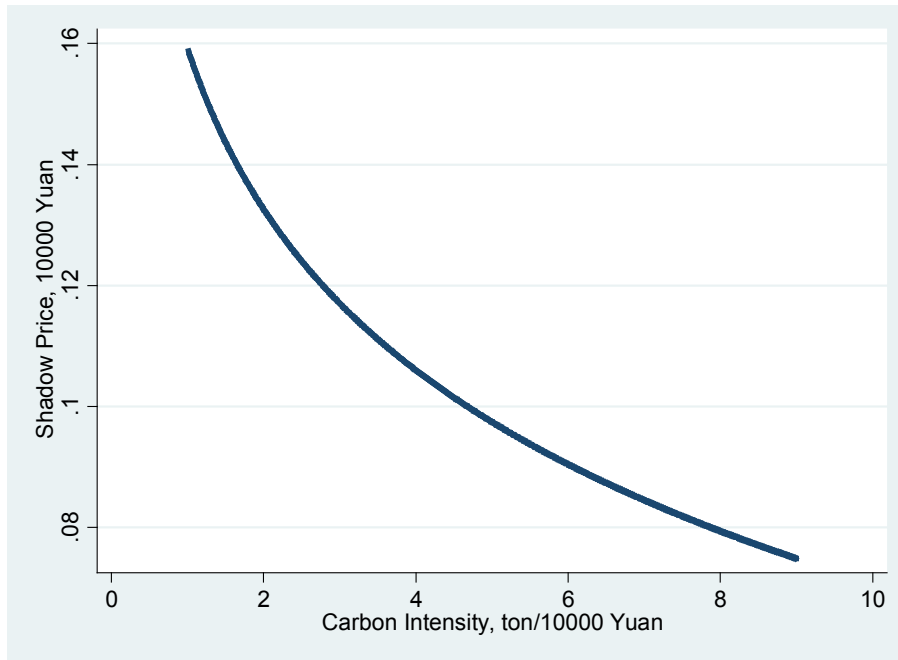


Figure 4: MACC in Logarithmic Functional Form

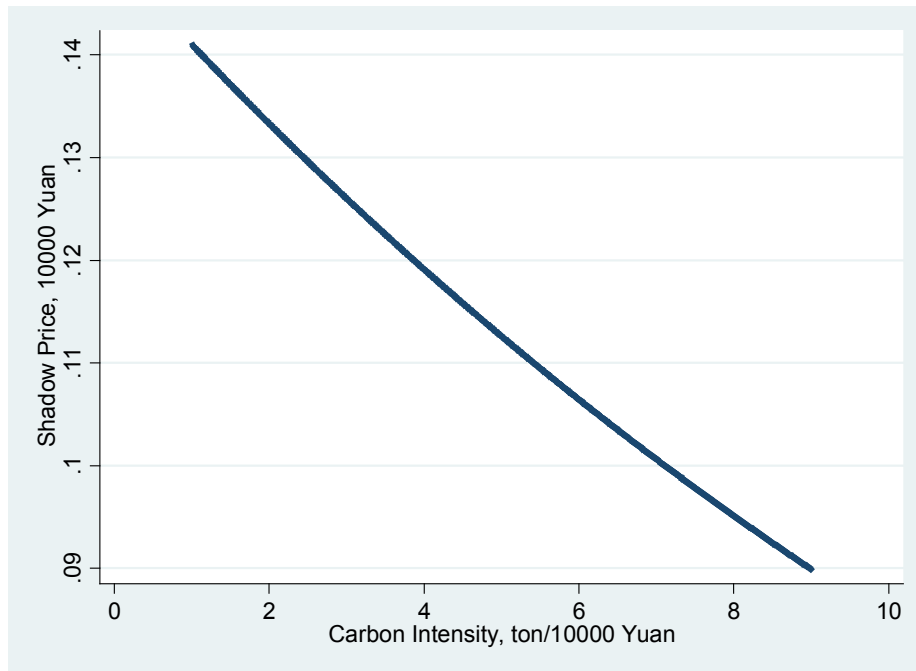


Figure 5: MACC in Exponential Functional Form

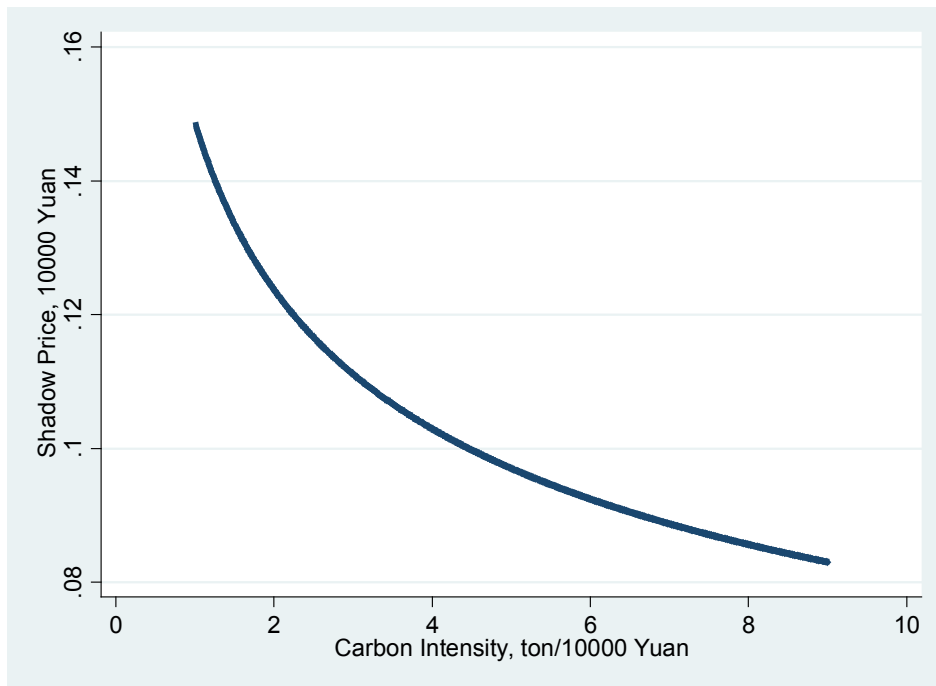


Figure 6: MACC in Power Functional Form