The Marginal Abatement Cost of Carbon Emissions in China

Chunbo Ma[*a], Atakelty Hailu[a]

[a] Centre for Environmental Economics and Policy,
School of Agricultural and Resource Economics,
The University of Western Australia, Crawley WA 6009.

*E-mail address: chunbo.ma@uwa.edu.au

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Abstract[†]

There is an emerging literature estimating the marginal cost of carbon mitigation in China using distance function approaches; however, empirical estimates vary widely in magnitude and variation, which undermines support for policies to curb carbon emission. Applying three commonly used distance functions to China's provincial data from 2001 to 2010, we show that the variability can be partially explained by the difference in the input/output coverage and whether the estimated marginal abatement cost (MAC) is conditional or unconditional. We also argue that the substantial heterogeneity in abatement cost estimates could be related to an economic interpretation that radial measures reflect the short-run MACs while non-radial measures reflect the long-run MACs. Our mean short-run MAC for carbon is 20 US$ per tonne, an amount that is very close to the carbon prices observed in China's recently launched pilot markets.

Key Words: Distance Functions; Marginal Abatement Cost; Carbon; China

[†] School of Agricultural and Resource Economics, University of Western Australia, 35 Stirling Highway, Crawley, WA 6009, Australia. Chunbo Ma thanks the University of Western Australia for funding through Research Collaboration Award. The authors thank Yiming Wei, Hua Liao, Ke Wang and other seminar participants at Beijing Institute of Technology and session attendants at IAEE Beijing conference for very useful comments and suggestions. All remaining errors are our own.

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Introduction

Climate change continues to be high on the international political agenda. As the world's top carbon emitter, China is a key player in climate negotiations and has been facing mounting domestic and international pressure to commit to a mandatory emission target. A sound understanding of the level and heterogeneity of marginal carbon abatement cost (MAC) across localities, sectors or even firms would inform policy makers about the potential cost advantage of a market based approach over the traditional command and control approach (Newell and Stavins, 2003).

The literature on the mitigation costs of greenhouse gases (GHG) has been extensively reviewed (Repetto and Austin, 1997; Weyant and Hill, 1999; Lasky, 2003; Fischer and Morgenstern, 2005; Kuik et al., 2009). A large part of this existing literature is based on the use of integrated systems forecasting models that derive the MAC of GHG emissions as shadow prices representing the economic growth that would be forgone in the pursuit of a Kyoto-based mitigation or stabilization target. These prices are often estimated for various future time horizons and for different sets of constraints and assumptions about the economic system. Such shadow price information is most useful for long-term planning and policy-making.

Another strand of the literature estimates the MACs as the shadow price of pollution mitigation within a distance function framework. These models use historical data and do not need to make widely varying and strong assumptions about future economic development and technological progress. As these estimates reflect recent evolutions in marginal abatement costs (MACs), they are more useful for identifying existing low cost opportunities for carbon reduction and for evaluating the potential cost savings from market-based policy instruments. That is, they are more relevant for immediate use or policy design exercises.

However, existing empirical estimates of the MAC of GHG mitigation in China obtained from these approaches vary widely and range from a few to thousands of US dollars per metric tonne. This variability in cost estimates undermines the scientific support for policy change as policy makers are usually reluctant to implement a mandatory GHG mitigation policy without a firm understanding of the true costs. In the last few years, there have appeared a few studies investigating China's GHG MAC estimates. Du et al. (2013) provides a thorough review of this literature which has mainly focused on carbon dioxide with a minor proportion of it investigating sulfur dioxide mitigation costs. Our study builds on this literature but makes a number of original contributions. We show that such variability can be explained by the differences in the coverage of inputs and outputs, the set of assumptions made on the production technology, the constraints imposed by various distance functions, and whether the MAC estimated is conditional or unconditional. We also compare estimated MACs with observed carbon prices from China's recently piloted carbon trading markets.

Firstly, given China's heavily coal-dependent energy structure and the way that carbon emissions were calculated in empirical literature, one would expect energy consumption and carbon emissions to be highly correlated. This high correlation would have significant distorting impact on the MAC estimates in studies including energy as a good output and carbon as a bad output. In cases where the correlation is high, it would be difficult to reliably estimate MACs. However, one can always get around the problem by aggregating inputs or removing the energy variable to allow for estimation and comparison across different approaches.

Secondly, all previous studies have either used primary energy use as the energy input or not provided a clarification of their energy input definitions. In this paper, we define energy input as the final rather than the primary energy consumption. It is important to make this clarification and use final rather than primary energy as the former is a more appropriate measure of the actual energy contributing to production. Using primary energy would overestimate the actual energy input in some provinces and underestimate it in others because energy demand and supply are not well matched across Chinese provinces. Some provinces produce and export while others import substantial secondary energy. In energy exporting provinces, primary energy used to produce secondary energy that is then exported should be counted as a raw material rather than as energy input. At the same time, imported secondary energy should be counted as part of actual energy input use in energy-importing provinces. In short, it is the final consumption, not the primary use, which defines the amount of energy that contributes to the final economic production of a province. Studies also differ in the calculation of GHG emissions. Some only account for energy-related GHG emissions while others also include emissions from production processes. The scope of emissions considered also influences the estimated MAC.

Thirdly, in recent years, economists have started to move beyond evaluating regulatory effects on a pollutant-by-pollutant basis since the interaction between different pollutant mitigation activities is important (Greenstone, 2003; Burtraw et al., 2003; Gamper-Rabindran, 2006; Considine and Larson, 2006). However, all previous studies on China's MAC of GHG mitigation have focused on a single undesirable output – either carbon dioxide or sulfur dioxide. Environmental policies often require simultaneous reduction of several pollutants. The MAC estimated from a distance function including a single bad output would be less informative about the overall compliance cost of such policies. The MAC estimated as such is unconditional marginal abatement cost and it is not appropriate to consider the sum of

MACs estimated individually as the overall compliance cost of simultaneous mitigation targets. Some airborne pollutants are highly correlated (i.e. jointly produced). For example, given China's heavily coal-dependent energy structure, a policy aiming to mitigate carbon emissions will often have the co-benefit of mitigating other pollutants such as sulfur dioxide, soot and dust. This will have a significant impact on the estimation of MAC. If multiple pollutants are jointly produced then the productivity impact that we associated with one pollutant should also be associated with other pollutants. The unconditional MAC of a pollutant may be very different from the MAC estimated conditional upon the emissions of other correlated pollutants remaining unchanged. A distance function including multiple bad outputs, on the other hand, allows estimation of conditional marginal costs and the overall cost of meeting simultaneous mitigation targets.

Lastly, the choice of distance function in the empirical literature is largely arbitrary. However, the MACs estimated are shown to be very much sensitive to the parameterization, the assumptions and constraints imposed, and the mapping schemes which are the paths in which the inputs or outputs are scaled toward the technology frontier in various distance functions (Vardanyan and Noh, 2006). Studies that do provide justifications for their choices often fail to consider the nature of the policy environment and associated interpretation of their results. Because the estimated MACs can be interpreted as the value of a pollution permit or allowance in a market environment (Coggins and Swinton, 1996), one can always compare estimated MACs with observed carbon prices in the market to assess the appropriateness of the production technology specification and other parameters of an empirical estimation. This was impossible in the past but is feasible now because of China's recently piloted carbon trading markets. This study provides the first comparison between observed and estimated carbon prices and reflects on the implications of the choice of production technology specification and mapping schemes within the distance function framework for shadow price estimation.

The paper is organized into five sections. The next section presents a review of the literature. The methods and data used in the study are described in the third section. The final two sections discuss the results and provide conclusions.

Literature

In spite of the size of China's carbon emission contributions and the significance of compliance cost that mitigation policies could impose, there is only a small number of studies investigating the MAC of carbon mitigation using a distance function approach. **Table 1** summarizes empirical estimates of China's MAC for carbon obtained using various distance functions. As shown in **Table 1**, all studies were conducted fairly recently. The results from these studies are not directly comparable as the studies differ in the chosen distance function, the period covered and the level of decision management unit (DMU). Nevertheless, the empirical estimates of the MAC of carbon emissions in China based on the distance function approach vary widely from merely a few US dollars into the hundreds and thousands of US dollars per metric tonne.

The non-parametric data envelopment analysis (DEA) approach is known to be less suited for the estimation of shadow prices due to its non-differentiability. For distance functions using a DEA approach, it is possible that some of the efficient observations are located on the inflection points or vertices, which means that there is no unique slope at those points. The choice of the slope inevitably affects the scale of the MAC estimated (Lee et al., 2002)

Table 1 – Empirical Estimates of China's MAC for Carbon (Distance Function Based Estimates)

Studies	Approach	Period	DMU	US$/ Tonne[†]
Wang et al., 2011	DEA	2007	Province	**77**
Choi et al., 2012	DEA	2001-2010	Province	**7**
Lee & Zhang, 2012	Input Distance	2009	Industry	**3**
Yuan et al., 2012	DEA	2004; 2008	Industry	**33~19561**
Wei et al., 2012	DEA	1995-2007	Province	**19**
Wei et al., 2013	Directional Output[††]	2004	Plant	**335**
Wei et al., 2013	Directional Output[††]	2004	Plant	**100**
Du et al., 2014	Directional Output	2001-2010	Province	**163~341**

[†]All monetary values converted to constant 2010 US dollars; [††]Wei et al. (2013) have estimated a deterministic directional distance function using linear programming and a stochastic directional distance function using maximum likelihood.

We thus focus on parametric distance functions which can be grouped into radial (Shephard) output or input distance functions and the relatively new directional distance functions. All output distance function values provide a measure of efficiency or productivity. In the presence of undesirable outputs, however, this measure can become ambiguous and the Shephard output-based measure ceases to be a meaningful measure of productive efficiency. This is because the output-distance measure is defined in terms of proportional expansion in outputs. But a proportional expansion in outputs is beneficial only if the expansion in desirable outputs will more than offset the damage caused by the accompanying expansion in undesirable outputs. While the directional output distance function allowing for simultaneous expansion of desirable outputs and the contraction of bad outputs does provide a meaningful measure of productivity (Chambers et al., 1998), Vardanyan and Noh (2006) show that the results can be sensitive to the chosen direction vector.

The directional distance function has been preferred over other parametric distance functions in estimating China's MAC (**Table 1**). The choice is often justified on the ground that the directional output distance function is a more appropriate metric for measuring performance in the presence of bad output under regulation (Färe et al., 1993; Färe et al., 2005). However, China's environmental regulation is mostly specified in terms of desirable inputs or outputs. In particular, before the pilot markets for carbon trading were introduced, China's regulations for mitigating carbon emissions were mostly specified in terms of the reduction in energy intensity. Energy intensity targets can be achieved by reducing energy consumption or increasing GDP growth with no binding power on carbon reduction. It is thus unclear whether the justification from the policy perspective is valid or not in the Chinese context.

Compared with output-based measures, input-based measure always provides a meaningful summary of efficiency because a proportional savings in inputs, with or without undesirable outputs present, is an unambiguous indicator of changes in social benefits (Hailu and Veeman, 2000). Lee and Zhang (2012) is the only paper on China that uses an input distance function and produces the lowest MAC for carbon in this literature as shown Table 1.

Radial and directional distance functions differ in the way the observed input/output vector is projected onto the frontier. Radial measures (i.e. Shephard output distance function and input distance function) keep the output or input mix fixed at observed (individual specific) proportions while non-radial measures (directional distance functions) apply the same direction vector to all data points and don't preserve the mix in the projection to the frontier. Drastic adjustments in the output structure are more likely in the long run than in the short run. Similarly, the long-run elasticities of inter-fuel and inter-factor substitutions are greater than the short-run ones. Thus one could think of radial distance function based measures as better approximations to short-run scenarios involving small adjustments while non-radial measures can be more useful for representing long-run situations where the input/output mix is transformed greatly. In this sense, it could be argued that the MACs estimated using radial and non-radial measures could have rather different interpretations.

In this study, we estimate China's MAC using three parametric distance functions – namely the input distance function (IDF), the output distance function (ODF), and the output directional distance function (ODDF). To ensure comparability, we apply all three to the same dataset and derive abatement cost estimates which are then compared with observed carbon prices in the pilot markets. Below, we describe the methods and data used in the study.

Methods

Like production, cost and profit functions, distance function provide a way of representing the underlying production technology (Shephard, 1953, 1970; Färe, 1988; Färe and Primont, 1995; Chambers et al., 1996). Some of their key attractive features are that they: can be used to model multi-output production processes; require only quantity data to estimate; do not require behavioural assumptions of cost, revenue or profit maximisation; have function values that are measures of (in)efficiency; and can be used to generate shadow prices or marginal abatement costs for undesirable outputs.

Given an underlying production technology Y(t) for period t, which is the set of technically feasible input (x^{it}) and output (u^{it}) vectors for producer *i*, or

$$Y(t) = \left\{(u^{it}, x^{it}) : x^{it} \text{ } can\, produce \text{ } u^{it} \text{ } in\, period \text{ } t\right\} \tag{1}$$

Shephard's (1953, 1970) radial input distance function is defined as the maximum amount by which an input vector can be radially (proportionally) contracted while still being able to produce the output vector:

$$IDF(u^{it}, x^{it}, t) = \max_{\theta}\left\{ \theta : \left(u^{it}, \frac{x^{it}}{\theta} \right) \in Y(t),\ \theta \in R^{+} \right\} \qquad (2)$$

The IDF value is by definition the reciprocal of the input-based measure of technical efficiency. A value of one for the input distance function indicates that the observed input-output vector is technically efficient (on the isoquant) while a value greater than one indicates that it is inefficient. That is, input-oriented technical efficiency (TE_x) is equal to:

$$TE_x = \frac{1}{IDF(u^{it}, x^{it}, t)} \qquad (3)$$

The function is a non-decreasing and continuous function of *x* for a non-negative vector of outputs *u*; it is concave and homogeneous of degree one in *x*; and it is a quasi-concave function of *u* (Shephard, 1953, 1970). And it is non-increasing in desirable outputs and non-decreasing in undesirable outputs (Hailu and Veeman 2000). Finally, the input distance function provides a complete representation of the production technology in the sense that

$$IDF(u^{it}, x^{it}, t) \geq 1 \Leftrightarrow (u^{it}, x^{it}) \in Y(t).$$

The radial output distance function is defined as the minimum amount by which an output vector can be radially (proportionally) deflated and still be producible with a given input vector:

$$ODF(u^{it}, x^{it}, t) = \min_{\theta}\left\{ \theta : \left(\frac{u^{it}}{\theta}, x^{it} \right) \in Y(t),\ \theta \in R^{+} \right\} \qquad (4)$$

The ODF value is the same as the output-based measure of technical efficiency. A value of one for the input distance function indicates that the observed input-output vector is technically efficient (on the production possibility frontier) while a value less than one indicates that it is inefficient. The output distance function has the following properties: it is a non-increasing function of x; it is convex and homogeneous of degree one in u; and it is a quasi-convex function of x (Shephard, 1970). The function is non-decreasing in desirable outputs but non-increasing in inputs and undesirable outputs (Färe et al., 1993) and characterizes the technology fully, or $ODF(u^{it}, x^{it}, t) \leq 1 \Leftrightarrow (u^{it}, x^{it}) \in Y(t)$. Output oriented technically efficiency (TE_y) is given by the value of the function:

$$TE_y = ODF(u^{it}, x^{it}, t) \qquad (5)$$

For empirical applications, the translog functional form has been used for radial distance functions. With the translog, the homogeneity property can be imposed globally as a restriction on the translog coefficients (e.g. Hailu and Veeman, 2000). In this study, the radial distance functions are specified as:

$$\begin{aligned} \ln DF(u,x,t) \; = & \; \alpha_o + \sum_{n=1}^{N} \alpha_n . \ln x_n + \sum_{m=1}^{M} \beta_m . \ln u_m + (0.5) \sum_{n=1}^{N} \sum_{n'=1}^{N} \alpha_{nn'} . \ln x_n . \ln x_{n'} \\ & + (0.5) \sum_{m=1}^{M} \sum_{m'=1}^{M} \beta_{mm'} . \ln u_m . \ln u_{m'} + (0.5) \sum_{n=1}^{N} \sum_{m=1}^{M} \gamma_{nm} . \ln x_n . \ln u_m \\ & + \alpha_t . t + (0.5) . \alpha_{tt} . t^2 + \sum_{n=1}^{N} \alpha_{nt} . t . \ln x_n + \sum_{m=1}^{M} \beta_{mt} . t . \ln u_m \qquad (6) \end{aligned}$$

where: output and input vector subscripts have been suppressed for simplicity; DF represents either IDF or ODF; n indexes the vector of inputs 1,2,...,N; m indexes the desirable and undesirable output vector 1,2,…,M; and t denotes the time trend variable. The translog function in (4) can be estimated using mathematical programming to minimise the sum of deviations from the frontier (distance function value of 1) subject to the appropriate monotoncity and homogeneity restrictions. To save space, we will not provide the details here as the reader can read the details in Fare et al. (1993) for output distance functions and in Hailu and Veeman (2000) for input distance functions.

The output directional distance function is defined in terms of translation or as the maximum amount by which an input/output vector can be translated along a chosen direction and still be technically feasible (or be a member of the technology set, Y(t)):

$$ODDF(u^{it}, x^{it}, t; g_u, g_x) = \max_\theta \left\{ \theta : \left(u^{it} + g_{u,} x^{it} + g_x \right) \in Y(t),\ \theta \in R \right\} \qquad (7)$$

Where: g_u is the output translation vector and would include positive value for desirable output and negative values for undesirable outputs; and g_x is the input translation vector and is negative. Like the radial functions, the ODDF generalizes the input and output distance functions (Chambers et al., 1996) and fully characterises the technology, $ODDF(u^{it}, x^{it}, t; g_u, g_x) \geq 0 \Leftrightarrow (u^{it}, x^{it}) \in Y(t)$. In all cases, the ODDF takes a value of zero when the observed point is efficient. A positive ODDF value signals that the point is inefficient and the directional measure of efficiency could be simply defined as the negative of the ODDF value:

$$TE_d = -ODDF(u^{it}, x^{it}, t; g_u, g_x) \qquad (8)$$

ODDF satisfies the following translation property which is useful in the estimation of the function (as is the homogeneity property in radial functions):

$$ODDF(u^{it} + \alpha g_u, x^{it} - \alpha g_x, t; g_u, g_x) = ODDF(u^{it}, x^{it}, t; g_u, g_x) - \alpha \qquad (9)$$

Other key properties of the ODDF include: it is non-increasing in desirable outputs but non-decreasing in inputs and undesirable outputs; it is concave in (u,x); and is homogeneous of degree -1 in the direction vectors, i.e.:

$$ODDF(u^{it}, x^{it}, t; \lambda g_u, \lambda g_x) = \lambda^{-1} ODDF(u^{it}, x^{it}, t; g_u, g_x)\ .$$

The ODDF is estimated using mathematical programming with the translation imposed on the estimated parameters. The flexible functional that is linear in parameters and also allows for imposing the property globally is the generalized quadratic (Färe and Lundberg, 2005; Färe et al., 2010; Hailu and Chambers, 2012). The generalized quadratic has the same structure as the translog function except that the input and output variable values are in levels (not logs). Its parameters are estimated using mathematical programming methods and constraints similar to those described in Hailu and Chambers (2012). In our case, we suppress the input direction vector (g_x=0) and estimate an output directional distance function with g_y vector that has positive elements for desirable and negative ones for bad outputs.

Finally, shadow prices for bad outputs can be derived from the different distance functions as implied marginal rates of transformation between a good output and a bad one transformed into dollar values using the market price for the good output (e.g. Fare et al., 1993; Hailu and Veeman, 2000). In our case, the shadow price r_j for a bad output u_j expressed in terms of a good output u_i, derived from an input distance function would be given by:

$$r_j = p_i . \left(\frac{\partial IDF(.)}{\partial u_j} \Big/ \frac{\partial IDF(.)}{\partial u_i} \right) \qquad (10)$$

where p_i is the market price for a good output while the good output is GDP as discussed below and this price would be unity. Similar formulae are used in the case of the radial output and the directional distance functions.

Data and Variables

Existing studies on the MAC of carbon dioxide all include energy as a separate production input variable. These studies typically calculate energy-related carbon emissions based on the IPCC reference approach (IPCC, 2006). Wei et al. (2013) also calculated emissions from the production of cement. Emissions calculated as such will inevitably exhibit high correlation with energy consumption (top left, **Fig.1**). Adding the carbon emissions from the production of cement will not reduce the correlation by much as the proportion of emissions from cement production is usually small compared with energy-related emissions (top right, **Fig.1**). In fact, the correlation is so high as to make the estimation of marginal effects via the radial measures extremely difficult and unreliable if not totally impossible[1]. **Fig.1** plots provincial CO_2 emissions in million tonnes (Mts), CO_2 emissions (with emissions from cement production) in Mts, SO_2 emissions in 10,000 tonnes, soot emissions in 10,000 tonnes against provincial final energy consumption in million tonnes of standard coal equivalent (Mtce).

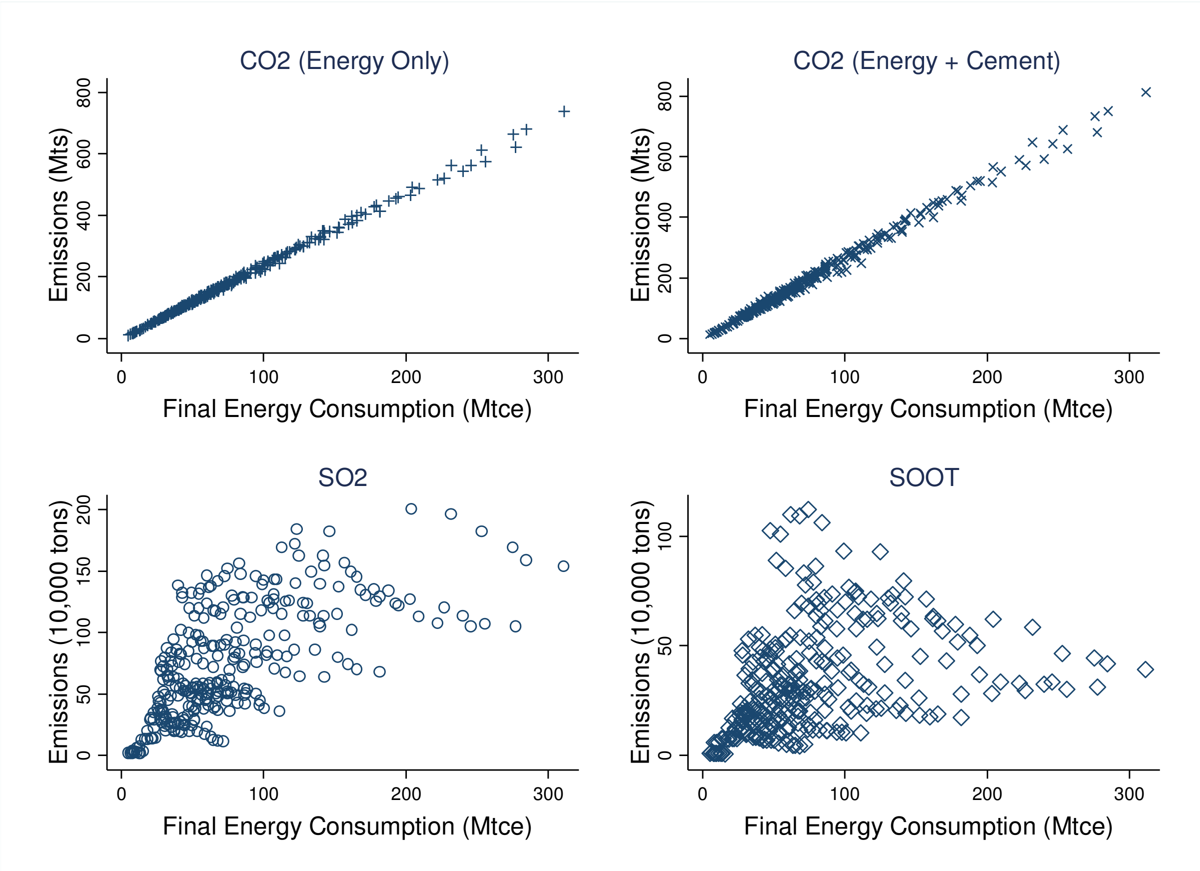

Fig. 1 – Provincial Final Energy Consumption and Emissions (2001-2010, 30 Provinces)

[1] Although not reported here, results from estimated distance functions with energy included as an additional input are available from the authors upon request.

To make results comparable across all distance function, we include two inputs (labor and capital), one good output (provincial Gross Domestic Product (GDP)), and three bad outputs – carbon dioxide (CO_2) emission, sulfur dioxide (SO_2) emission, and total provincial soot emission. We use Chinese provincial data for the 10-year period from 2001 to 2010. **Table 2** presents the definition and summary statistics of these variables. Below we explain how the data was collected and constructed.

Inputs

Labor data was collected from *China's Statistical Yearbooks* (CSYs) (NBSCa, 2002-2011). Provincial capital data were collected from Wu (2009) with updates for recent years obtained from the author.

Outputs

Provincial GDP were collected from *China's Statistical Yearbooks* (CSYs) (NBSCa, 2002-2011). Emission data on SO_2 and soot are available from *China's Environmental Statistical Yearbooks* (NBSCb, 2002-2011). China's statistical authority does not report emission or inventory data on carbon dioxide. Most existing literature follow the IPCC reference approach to estimate carbon emissions based on energy consumption. We followed the same practice to calculate energy-related carbon emissions; however, we calculate CO2 emissions based on final energy consumption rather than primary energy consumption as noted previously. We also calculated carbon emissions from the process of cement production. Carbon emission factors for the burning of coal, oil and natural gas and the production of cement are available from the IPCC (2006). Emission factors for heat and electricity were calculated as share-weighted emission factors of individual energy carriers. Energy shares of coal, oil and natural gas used in heat provision and electricity generation were collected from *China's Energy Statistical Yearbooks* (NBSCc, 2002-2011)[2].

The total energy consumption is the sum of the final consumption of five energy carriers: coal, oil, natural gas, heat and electricity. *China's Energy Statistical Yearbooks* (NBSCc, 2002-2011) report three different provincial energy statistics: total consumption by energy carrier, total primary energy supply and total final energy consumption. The first two are similarly defined as the total energy resources that are available and consumed by a province in a given year, which includes both resources used for energy transformation and raw materials, and resources actually used by the economy as final energy consumption. As we argued in the introduction, it is the final consumption, not the primary energy that defines the amount of energy that contributes to the economic production. We have thus collected total final energy consumption by energy carrier. All energy consumption data were converted to standard coal equivalent (SCE) – the standard energy metric used in Chinese energy statistics. *China's Energy Statistical Yearbooks* also provide conversion factors for all energy carriers based on equivalent calorific values. However, we chose to convert heat and electricity consumption to SCE based on coal equivalent in heat supply and electricity supply (i.e. supply efficiency factors) rather than calorific values. This is because the former is a better reflection of the energy transformation efficiency and the actual primary energy consumed in heat provision and electricity generation. We collected province-year-specific efficiency factors for heat and electricity provision from various issues of *Statistical Compilation of China's Electricity Industry* (CEC, 2001-2010).

[2] As this is the common practice of constructing the emission data of carbon dioxide, we do not report the detailed calculation process. Data is available from the authors upon request.

Table 2 – Summary Statistics for Data Used in the Analysis (2001-2010, 30 Provinces)

Variables	Definition†	Unit	Mean	S.D.	Min	Max
Inputs						
Labor	Total employment	10^6 persons	23	15.2	2.4	60
Capital	Total capital stock	10^6 $US††	436	358	41	2138
Outputs						
GDP	Gross Domestic Product	10^9 $US††	135	120	7	694
CO_2	Energy related CO_2	10^6 metric tonnes	184	131	10	738
CO_2^c	CO_2 with cement	10^6 metric tonnes	204	147	12	813
SO_2	SO_2 emission	10^4 metric tonnes	75	46	2	200
Soot	Soot emission	10^4 metric tonnes	34	24	1	112

†All variables defined as annual provincial statistics; ††all monetary variables converted to constant 2010 prices and RMB is converted to US dollar at 1US$=6.6227RMB.

Carbon Prices

China has already launched seven regional pilot markets for carbon trading in a bid to gain experience ahead of a nationwide scheme. The pilot markets include Beijing, Shanghai, Tianjin, Guangzhou, Shenzhen, Hubei and Chongqing. Daily trading prices for these pilots are available from http://k.tanjiaoyi.com/ .

Results and Discussions

Input and Output Coverage

We estimated MACs using different distance functions and with different input and output coverage levels. **Fig.2** presents the 10-year provincial mean MACs estimated using an input distance function for the following four cases: 1) *Single Bad* which includes only energy-related CO2; 2) *Single Bad WC* which also includes CO2 from cement production; 3) *Multiple Bads* which include CO2, SO2 and soot); and 4) *Multiple Bads WC* where carbon emissions from cement production are also included.

The provinces are sorted in increasing order by the last (i.e. *Multiple Bads WC)* MAC values. A broader sectoral coverage reduces the marginal abatement cost estimates. The MAC for carbon is consistently lower if carbon from cement production is included. This is true for both the calculations with only carbon (solid and dashed curves) and those with multiple bads (dotted and long-dashed curves).

As indicated in the introductory section, the MACs estimated with a single bad output and multiple bad outputs can be interpreted as, respectively, unconditional and conditional marginal abatement cost. From a policy perspective, unconditional MAC is less informative when policy makers today are more interested in knowing the overall compliance cost of simultaneous mitigation targets. For a country like China which is heavily dependent on coal consumption, a policy aiming to mitigate carbon emissions often has the co-benefit of mitigating other pollutants such as sulfur dioxide, soot and dust. Conditional MACs should therefore be lower than unconditional MACs in this case. This is also confirmed by our results in **Fig.2**. The MACs estimated with multiple bad outputs are consistently lower than their counterparts with single bad outputs. Although not reported here, these same observations hold for output distance function and output directional distance function as well.

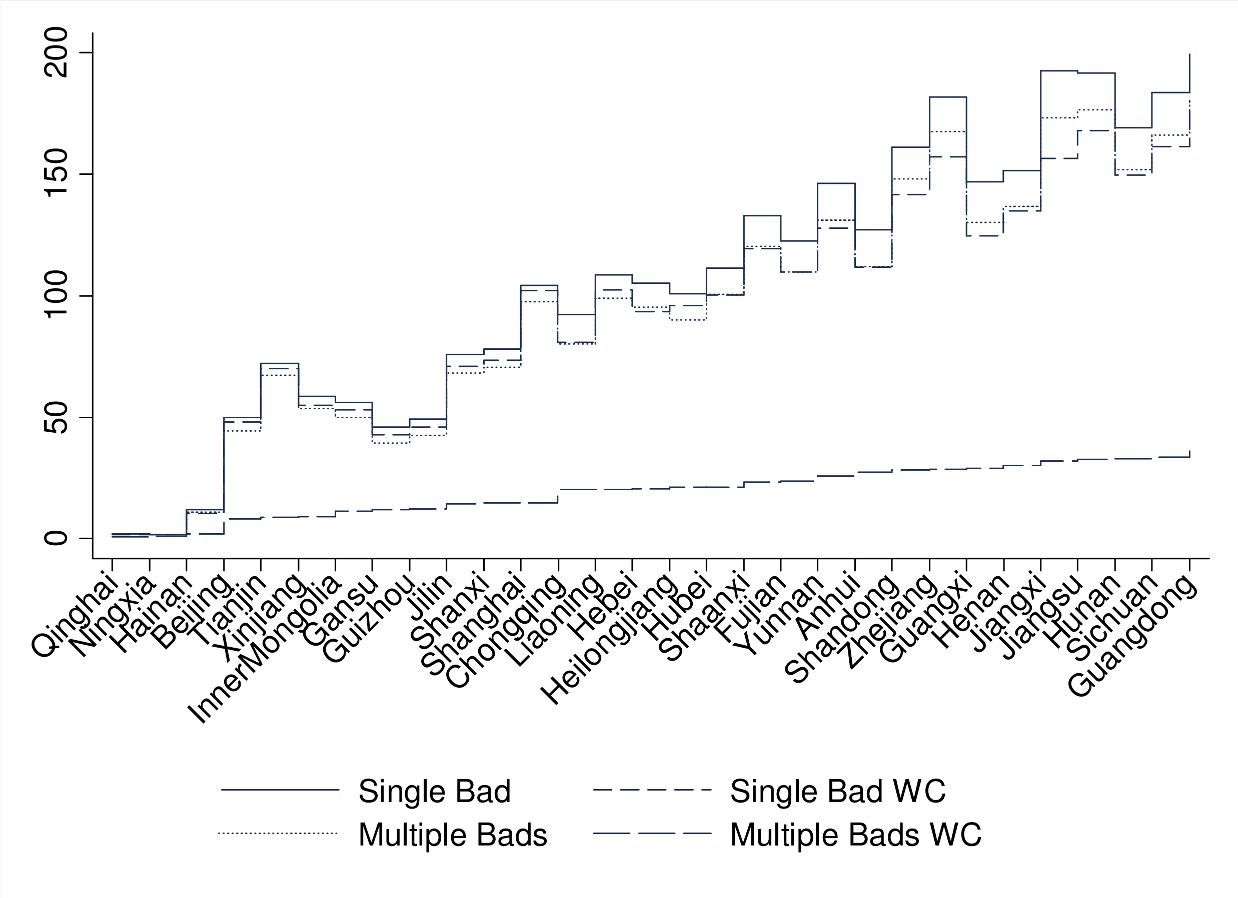

Fig.2 Provincial MAC Curves (US$/Tonne)

Cross-Consistency in Efficiency and MAC Estimates

Here we show results from three distance functions (IDF, ODF and ODDF) with all three bad outputs and with carbon emissions from cement production included. **Fig.3** plots efficiency estimates. There is generally good consistency across all three distance functions, although radial measures (IDF and ODF) produce more consistent efficiency estimates. Note that larger bubble indicates greater provincial GDP. The fact that we obtain very similar results applying different distance functions to the same dataset adds to the confidence that the outcomes reflect genuine efficiencies rather than artifacts of the choice of specific distance functions. However, this is not the case for the MAC estimates. **Fig.4** shows the 10-year provincial mean MAC estimates using different distance functions. The provinces are sorted by MAC values estimated from ODDF. We make the following observations.

- With our data, the two radial measures – IDF and ODF – produce identical MAC estimates; however, this is not the case with other data sets.
- There is a low correlation between MAC estimates from radial (IDF or ODF) and non-radial distance functions (ODDF). In fact, the correlation between the two series of provincial mean MACs is only 0.37. Comparisons across studies typically focus on mean estimates (**Table 1**) but the ranking and distribution are also important. The low correlation suggests that different distance functions could possibly identify different provinces as low MAC sources of abatement, which is especially problematic for drawing out policy implications.
- There is also substantial heterogeneity in the variation and magnitude of MACs estimated using different distance functions. The variation and magnitude of MACs estimated from ODDF are significantly greater than those obtained from IDF or ODF. The grand mean MAC estimate from ODDF is 340 US$ which is generally consistent with the estimates in Wei et al. (2013) and Du et al. (2014). The mean MAC estimate from IDF or ODF is merely 20 US$, which is higher than the estimate (3 US$) in Lee and Zhang (2012) but nowhere near the ODDF estimate. Although Lee and Zhang also use an IDF, they use industrial data rather than provincial data.

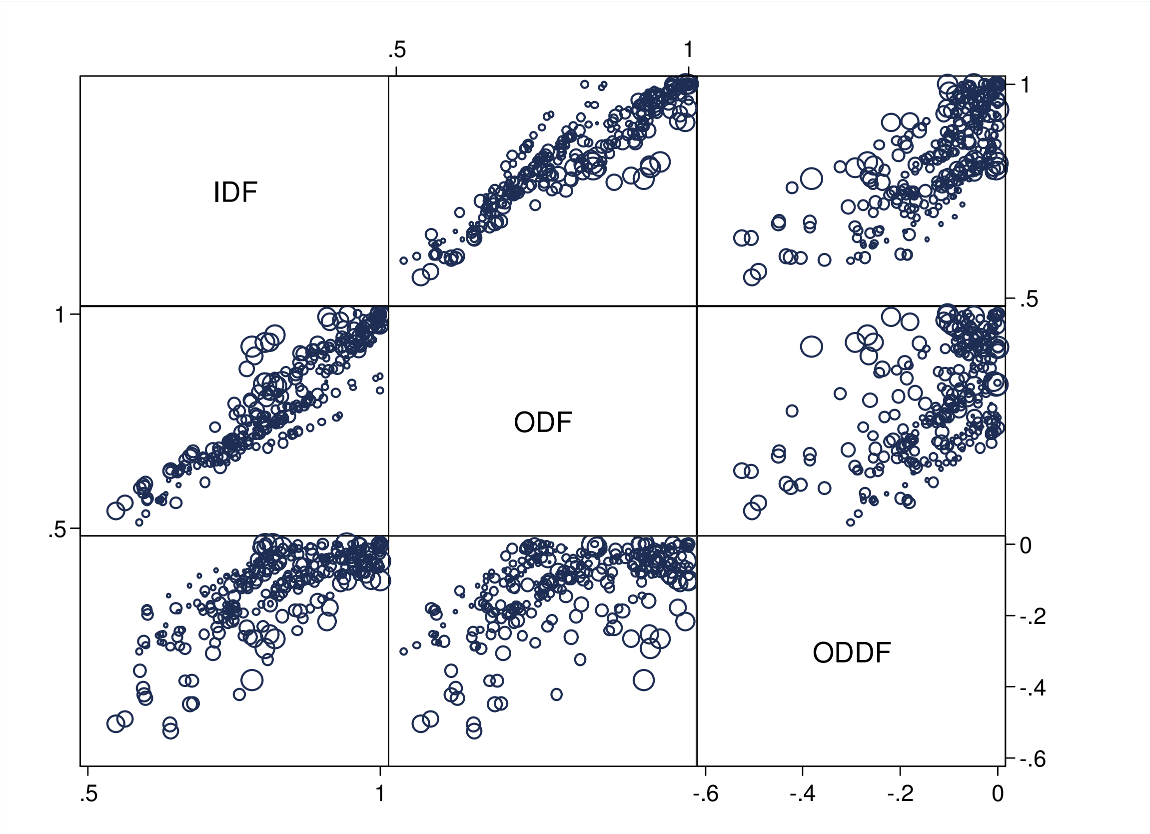

Fig.3 Cross-Consistency of Efficiency Estimates

Market Observations

Studies using ODDF often justify their choice on the ground that ODDF is a more appropriate metric for measuring performance in the presence of bad output under regulation. However, for our chosen study period, China did not have any direct regulation imposed on carbon. The literature also attempts to reconcile the substantial difference between MAC estimates using ODDF and those using IDF or ODF from a methodological perspective. The ODDF derives much higher MAC estimates because it places the DMUs on a steeper portion of the production frontier than the IDF or the ODF. However, the economic interpretation is often unclear. Given the price levels observed in the European and Australian carbon markets and the fact that China remains largely a developing country, the mean MAC of 340$ per tonne estimated using ODDF seems too high.

It is important to note that radial measures (IDF and ODF) keep the output or input mix constant while non-radial measures (e.g. ODDF) don't. Drastic adjustments in the output structure or inter-fuel and inter-factor substitution are more likely in the long run than in the short run. We argue that radial measures are most likely approximating the short-run scenarios while non-radial measures reflect long-run situations. China has only recently launched its seven pilot markets for carbon trading (Shenzhen, Beijing, Shanghai, Tianjin, Guangzhou, Chongqing and Hubei). Carbon prices observed in these spot markets therefore reflect short-run MACs[3]. **Fig.5** illustrates complete carbon price trends in the pilot markets. As can be seen from the figure, observed carbon prices mostly lie within the range of 5 to 15 US$ per tonne. This is much closer to the mean MAC of 20 US$ we obtain from our radial distance functions than the directional distance function[4].

[3] The reference to observed carbon prices is made for comparison purposes only. It is not necessary that the estimated prices are similar or close to observed prices since the observed prices might not reflect the true opportunity costs of carbon because of low participation. There is also substantial heterogeneity in term of participation and liquidity across the seven pilot markets. While recognizing the limitation of liquidity, a report recently released at the 2014 United Nations Climate Change Conference held in Lima indicated that carbon prices in China have converged to a range between 20 to 70 Yuan per ton after a year of operation, which is strongly indicative of future price fluctuation ranges for a national carbon market (Wang et al, 2014).

[4] The fact that our estimate is slightly higher could be due to two reasons. First, our CO_2 calculation only considers energy-related emissions and emissions from cement production. The CO2 emissions covered in China's pilot trading schemes are much broader. Most schemes cover traditionally energy-intensive and emission-intensive manufacturing industries and some also include building and construction and tertiary industries. A broader coverage would drive down the marginal abatement cost.

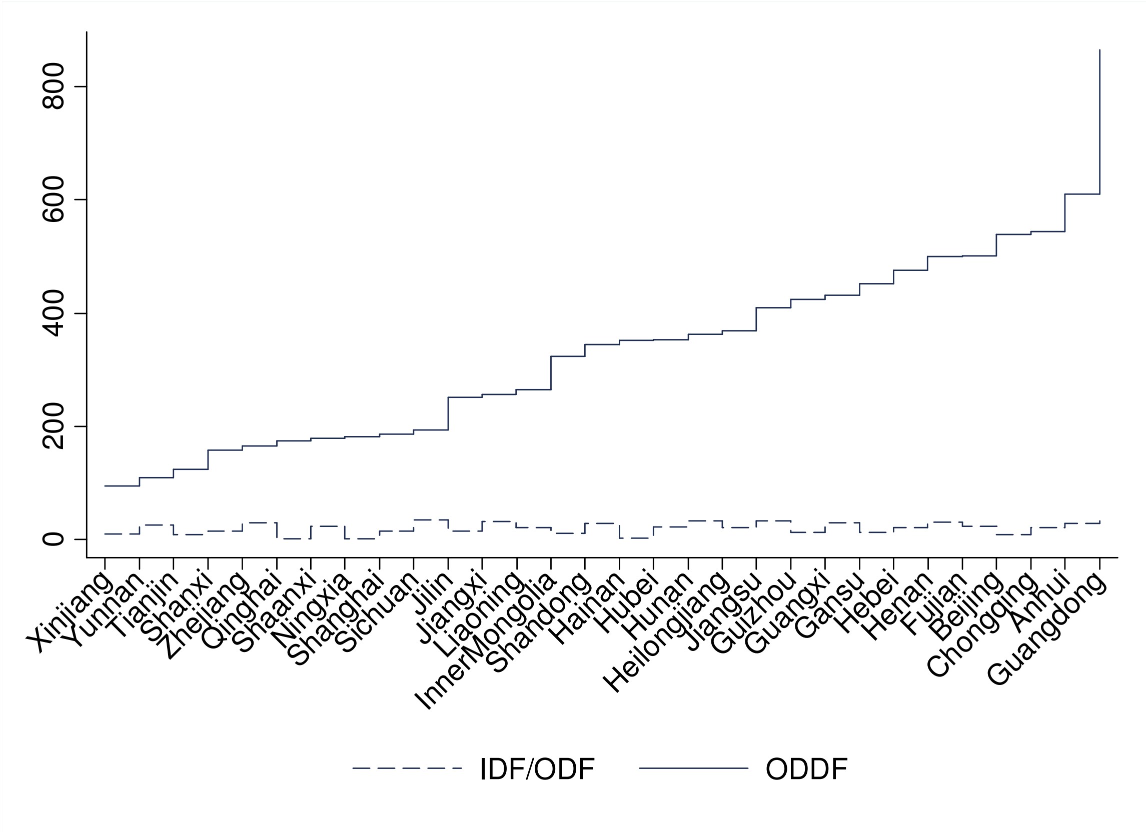

Fig.4 Cross-Consistency of MAC Estimates (US$/Tonne)

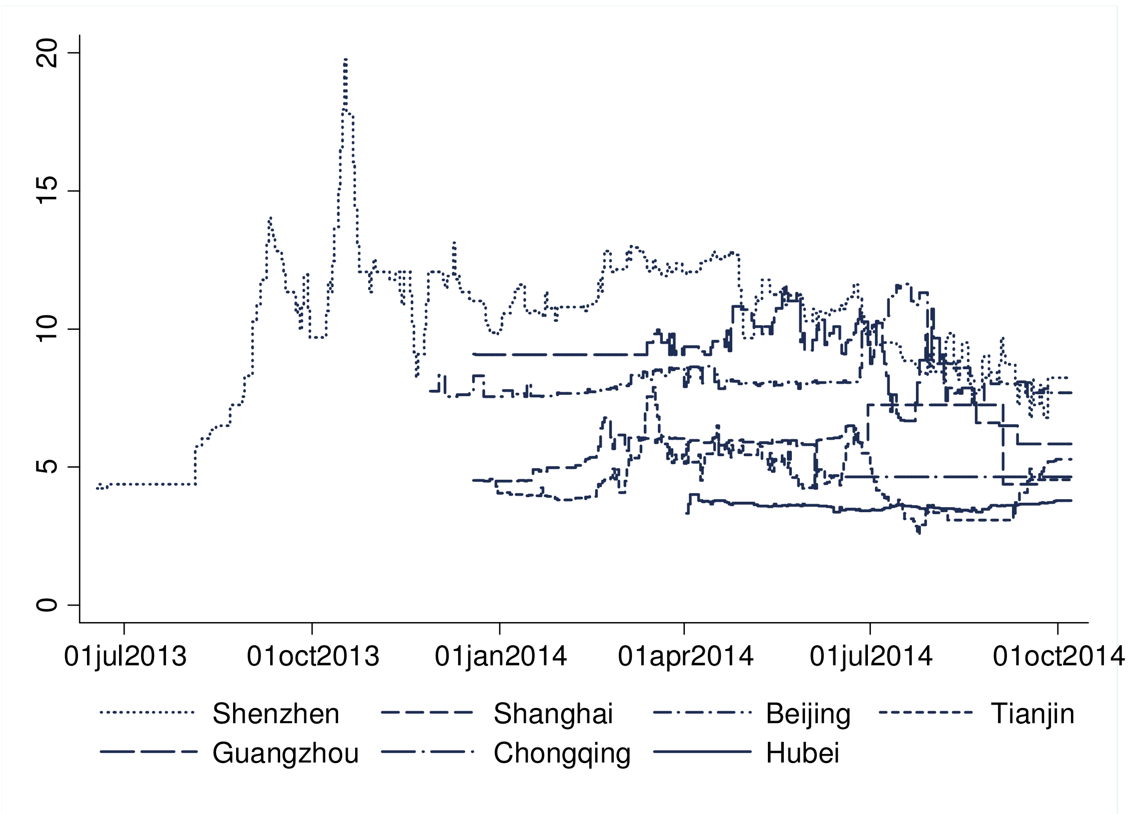

Fig.5 Carbon Prices in China's Pilot Markets (US$/Tonne)

Because directional distance functions allow structural change in outputs and inputs, they may provide long-run MAC estimates. However, the MAC estimates are very sensitive to the chosen mapping scheme (Vardanyan and Noh, 2006). More importantly, the economic interpretations are rather different with different mapping schemes. Researchers are strongly encouraged to interpret their results in the context of the data and the particular methods employed to derive shadow prices. Caution needs to be taken when generalizing results or comparing across studies.

Bootstrapped Results

The mathematical programming approach allows us to impose the theoretical restriction in the estimation process and have them satisfied at all data points. To explore the sensitivity of the results, we bootstrapped the distance function results for all the models. **Fig. 6** presents the boxplots of results from 5,000 bootstraps for three distance functions (IDF, ODF and ODDF) estimated with all three bad outputs included (CO_2, SO_2 and Soot). The bootstrapped means are very consistent with the grand means of our original estimates and the mean values from IDF and ODF are still substantially lower than that from ODDF. We have also presented detailed bootstrap results from ODDF for all 300 observations (**Fig. 7**). Our original MAC estimates are very close to the mean values and fit well within the upper and lower 95 quantiles of bootstrapped results even at the individual observation level.

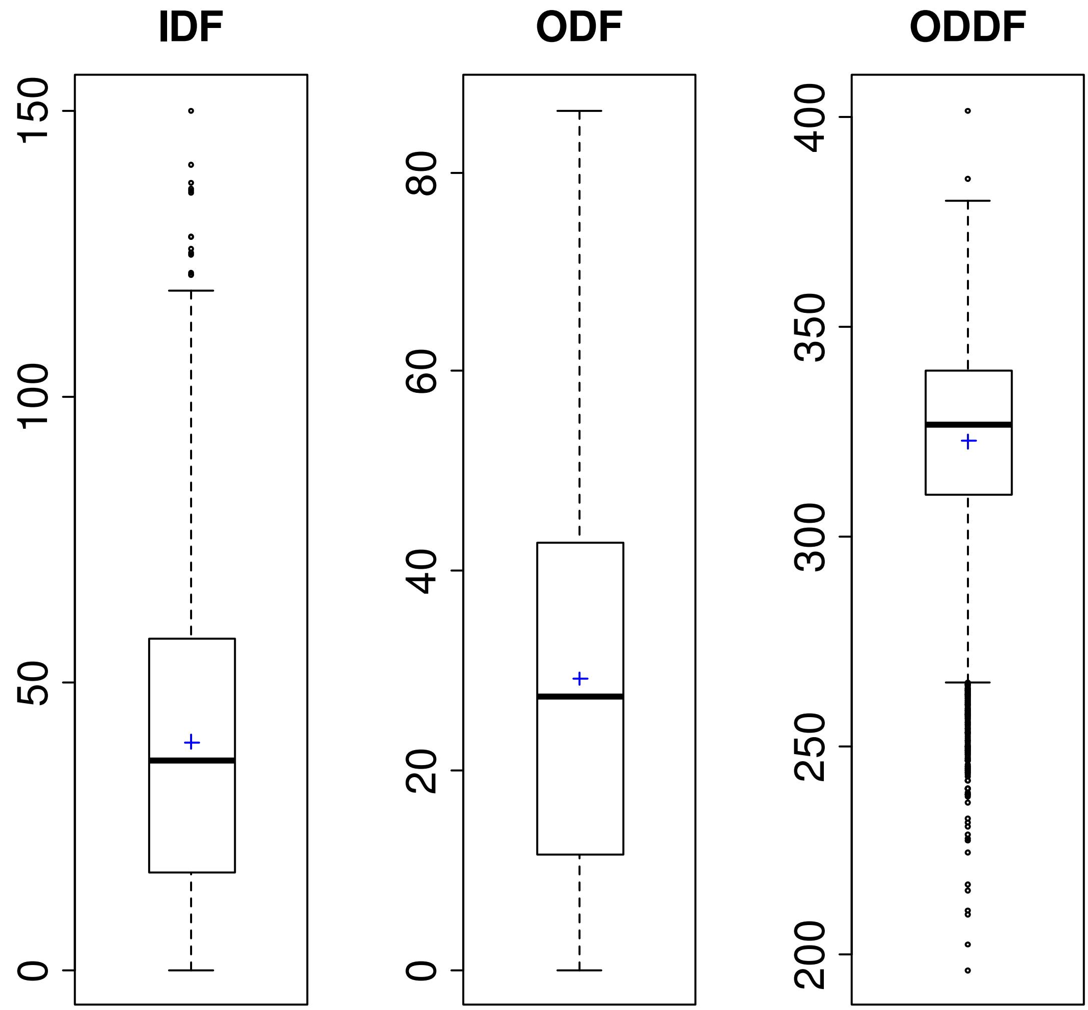

Fig.6 Distribution of Bootstrapped MAC Estimates (US$/Tonne)

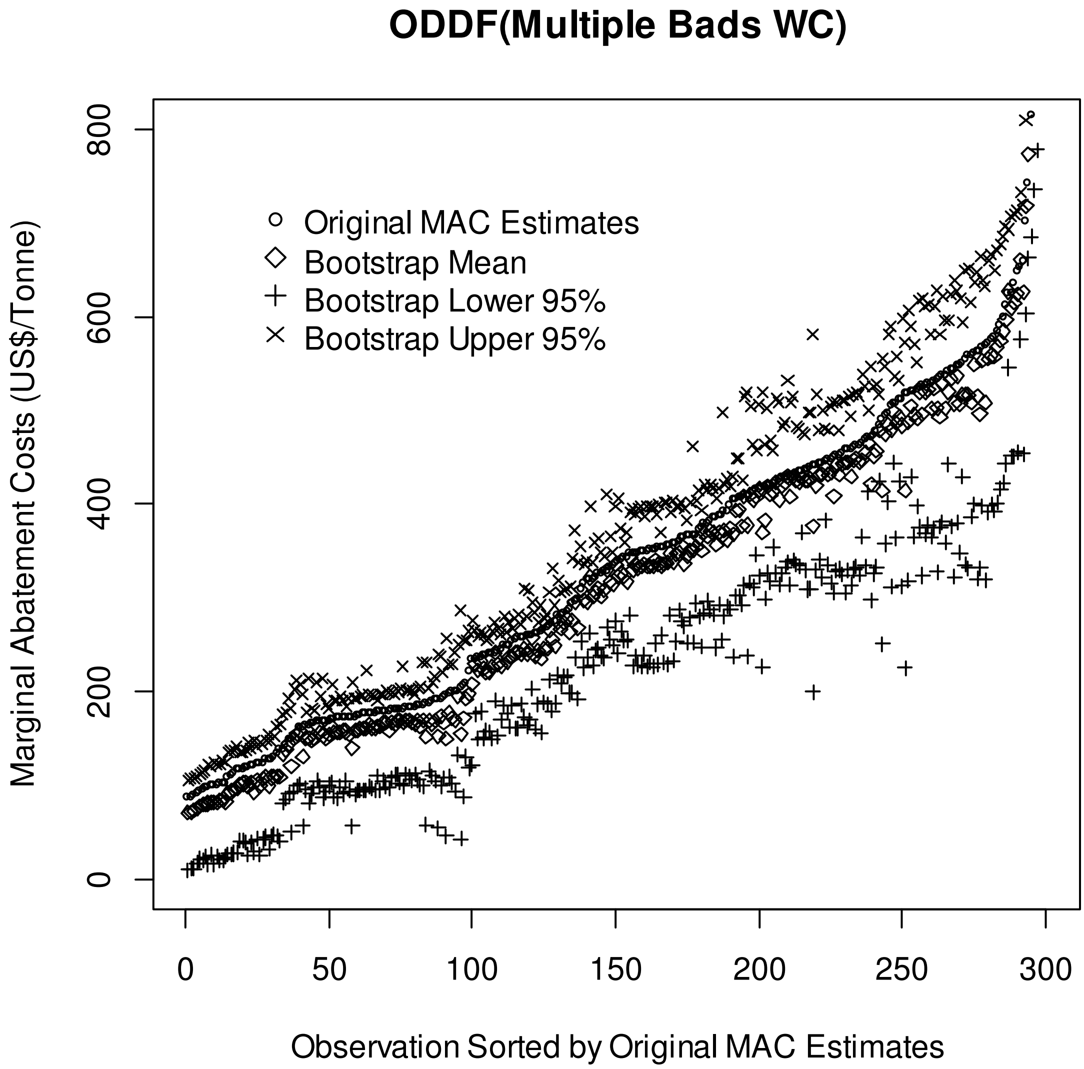

Fig.7 Distribution of Bootstrapped MAC Estimates by Observation (US$/Tonne)

Conclusions

A growing number of countries are considering economic instruments such as pollution taxes or tradable permits to tackle environmental problems. One of the major challenges governments face is the lack of adequate knowledge about the cost to industry of pollution abatement activities. Such cost estimates are either unavailable or uncertain. In the case of

China, for example, empirical estimates of the marginal abatement cost (MAC) of carbon mitigation obtained using distance function approaches vary widely. This variability in the magnitude and ranking of MAC estimates may undermine the scientific support for policies aimed at curbing carbon emission. In the literature, there has been very limited work that would shed light on this variability to help governments make sense of the wide gaps between estimates and also between these estimates and real-world prices for carbon. In this paper, we show that the variability can be partially explained by the differences in the input/output coverage of estimated models and by whether the MAC estimated is conditional (or unconditional) on simultaneous reduction of other related pollutants. The paper also argues that the substantial heterogeneity in cost estimates can be explained in terms of inherent differences in the nature (or economic interpretation) of the estimates from different studies. In particular, we argue that radial measures imply little change in the input or output mix and thus reflect short-run MACs while non-radial measures are evaluated at input/output mixes that are a transformation of observed values and therefore are more akin to long-run MACs. Finally, we provide short-run estimates that are very close to the carbon prices observed in China's recently launched pilot markets. The findings in our study suggest that a promising avenue for future research would be a careful investigation of the economic interpretations of abatement cost estimates generated by different methods or mapping schemes (radial, directional, etc.); such an exercise would facilitate comparisons across different estimates and help policymakers get a better sense of the cost to industry of pollution reduction measures.

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