Abatement costs of Emissions from Crop Residue Burning in major crop producing regions of China: Balancing food security with the environment

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Selected Paper prepared for presentation at the 2016 Agricultural & Applied Economics Association Annual Meeting, Boston, Massachusetts, July 31-August 2

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Abstract
This paper estimates the shadow price of CO2 from burning crop residue in the Chinese agricultural sector and explores the policy implications for decision makers. Using a parametric translog directional distance function, we evaluate the technical efficiency and shadow prices of CO2 reduction for 7 major maize provinces in China from 1996-2013. Our results show that crop yield, cost of total inputs, and percentage of burnt crop residue account for 30%, 10% and 20% of the inefficiency, respectively. The shadow price of CO2 from burning crop residue is estimated to range from 0-1.368 yuan/ha (or US$210.5/t) with an average of 0.496 yuan/kg (or US$76/t). Further analysis indicates that the average efficiency will increase by 9% if conservation practices are adopted by assuming 10% decrease in yield and 50% decrease in burnt crop residue under conservation practices compared to conventional practices. The shadow prices in these two cases imply that the whole society will benefit if the government spends less than 201 yuan/ha to promote adoption of conservation practices. This government offset would compensate farmers for yield reductions in favor of implementing conservation practices that would substantially reduce CO2 emissions.
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Lingling Hou\textsuperscript{1}, Dana Hoag\textsuperscript{2}, Catherine Keske\textsuperscript{3}

1. Introduction

Agriculture is a major contributor to global emissions of the greenhouse gases (GHGs) that drive climate change. World agriculture accounted for an estimated direct emission of 5.1-6.1 Pg CO\textsubscript{2}-equivalents year\textsuperscript{-1}, contributing 10-12\% to the total global anthropogenic emissions of GHGs in 2005 (Smith et al., 2007). The direct and indirect (including producing agricultural inputs) account for about 40\% of total global GHGs. That makes the agricultural sector the world’s second-largest emitter, after the energy sector (which includes emissions from power generation and transport). China, which is predominantly rural and agricultural, is one of the largest producers of agricultural emissions in the world. Greenhouse gas (GHG) emissions in China reached approximately 820 MtCO\textsubscript{2}e.

The practice of burning crop residues in China is a major source of CO\textsubscript{2} emissions in agricultural sector. Sun et al. (2016) estimates that about 2.7 billion tons of CO\textsubscript{2} had been emitted by farmers’ burning crop residues in farm fields in China from 1996-2013, which was about 45\% of the total residential coal consumption over the same period. In Northeast China, more than 80\% of crop residues each year are burned in field, of which over 2/3 is from maize straw. After the harvest reason, burning crop residues not only harms human respiratory system, but also often results in low visibility that delays air flights and impedes ground transportation. Ostensibly, a change in agricultural management practices might lower the social costs of air pollution.

It is promised that by 2030 China will reduce 60-65\% of CO\textsubscript{2} intensity (tons per dollar of GDP) compacted to 2005. Although scholars predict that China’s agricultural sector has the potential to reduce GHGs by 20\%, how to allocate abatement missions among sectors are still a critical question to policy makers. Theoretically, the optimal abatement scheme is to maximize the
total GDP given the constraint of abatement mission. This will result to an abatement level where marginal cost of each sector is equal. Therefore, it is important to estimate the abatement cost for each sector. Crop production is the top agricultural land use. We will focus on maize production in this preliminary draft manuscript. Later we will extend our analysis to wheat and rice production.

Crop management practices such as conservation tillage offer the greatest reduction potential. Conservation tillage is a range of cultivation techniques (including minimum till, strip till and no-till) designed to minimize soil disturbance for seed placement, by allowing crop residue to remain on soil after planting. Conservation tillage has other co-benefits as well, such as protecting soil from wind and water erosion. Several provinces in China, with the support from the Ministry of Finance (MOF) and the Ministry of Agriculture (MOA) recently piloted on Compensation for Soil Conservation Program (CSCP). The government wonders how much investment is appropriate to promote such programs. However, national and international markets do not exist for GHGs in most cases. Furthermore, measuring GHG emissions from individual farms can be elusive, making cost-benefit analysis challenging. Crop production is an important component of food security, and simulation can be a useful tool for providing the government with information about potential impacts of management changes on crop yields. This paper provides the government with a reference to make an informed decisions about CSCP.

In the literature, many studies exist on estimating abatement cost of undesirable outputs, such as CO2, with the concept of shadow prices. However, there is little literature to estimate the shadow prices in of agricultural emissions in China. Zhou et al. (2014) conducted a systematic review of the studies on estimating shadow prices of undesirable outputs with efficiency models. These studies were primarily focused on energy generation. The shadow price of undesirable output can be interpreted as the opportunity cost of abating one additional unit of undesirable output in terms of the loss of one unit of desirable output. A prevalent practice is to use the Shephard or directional distance function to derive the shadow price, which can be further calculated by parametric or nonparametric efficiency models. In application, the
earlier studies have estimated shadow prices of GHGs at the plant, sector and even regional economic levels. Wei et al. (2013) estimates the shadow price of CO$_2$ and explores its determinants for thermal power enterprises in China. The mean value of the CO$_2$ shadow price is $249 in 2004 using linear programming approach. They also found that the shadow price is a negative function of firm size, age, and coal share, and is positively correlated with the technology level. Du et al. (2015) investigated the technical inefficiency, shadow price and substitution elasticity of CO$_2$ emissions of China based on a provincial panel data from 2001-2010. They show that China’s technical inefficiency increases over the period implying further scope for CO$_2$ emissions reduction in the medium and longer term at best by 4.5% and 4.9% respectively. The shadow price of CO$_2$ abatement increases from 1000 yuan/t in 2001 to 2100 yuan/t in 2010.

The paper is the first to estimate the CO$_2$ shadow price associated with the practice of burning crop residue in China. The directional distance function in translog form is used to quantify the efficiency and CO$_2$ shadow price for 7 major maize production provinces from 1996-2013. The paper also simulates the efficiency and abatement cost of CO$_2$ under a scenario of adopting soil conservation practices.

From a policy perspective, the results of our research are expected to be of great interest and use to decision makers as a decision support tool, since they provide the first CO2 shadow price estimates in the framework of burning crop residues. This paper also contributes to the literature about abatement costs of agricultural emissions. Being able to assess the marginal abatement costs is an important first step in environmental policy issues, since these costs can be used when fixing carbon tax rates and ascertaining an initial market price for a trading system(Fare et al, 1993; Wei et al., 2013). Furthermore, by comparing the two cases, this paper provide how much the government should invest to promote soil conservation practices.

2. Theoretical model and empirical specifications

We follow Färe et al. (2005) and Hou et al (2015) to present the shadow pricing model based on a directional output distance function. In the first step of this approach, the directional
distance function, which underlies production technology, is constructed through an output possibility set. Then shadow prices of undesirable outputs are derived by setting the marginal rate of transformation between desirable and undesirable outputs equal to their price ratio. Finally, the estimation process of this model is presented.

2.1. Directional Output Distance Functions

Before deriving the shadow prices by a distance function approach, it is necessary to first describe the directional output distance function. A directional distance function corresponds precisely to one production possibility set. The technologies for different cropping systems that produce desirable outputs and undesirable outputs jointly are represented by a production possibility set

\[ P(x) = \{(y, b): x \text{ can produce } (y, b)\} \quad (1) \]

where \( x = (x_1, ..., x_N) \in \mathbb{R}^N_+ \) is a vector of \( N \) inputs, \( y = (y_1, ..., y_M) \in \mathbb{R}^M_+ \) is a vector of \( M \) desirable outputs and \( b = (b_1, ..., b_J) \in \mathbb{R}^J_+ \) is a vector of \( J \) undesirable outputs.

The production possibility set \( P(x) \) underlies all feasible input-output combinations. It also illustrates the trade-offs between desirable and undesirable outputs. The production possibility set has the following properties:

1. \( P(x) \) is compact and closed, with \( P(0) = \{0,0\} \).
2. Strong disposability of desirable outputs and inputs, i.e. if \( (y, b) \in P(x) \), then for \( y' \leq y, \ (y', b) \in P(x) \), and if \( x' \geq x \), then \( P(x) \subseteq P(x') \).
3. Weak disposability of desirable and undesirable outputs, i.e. if \( (y, b) \in P(x) \) and \( 0 \leq \theta \leq 1 \), then \( (\theta y, \theta b) \in P(x) \).
4. Null-jointness: if \( (y, b) \in P(x) \) and \( b = 0 \), then \( y = 0 \).

The first two properties are standard assumptions in production theory by Shephard (1970). The first assumption implies “no free lunch;” finite inputs produce finite outputs. The second
assumption of strong disposability means that inputs and desirable outputs can be disposed of at no costs. Specifically, it implies that fewer outputs can be produced by the same amount of input, and if inputs are increased, outputs will not shrink. Two nonstandard assumptions on desirable and undesirable outputs are also imposed. Weak disposability of desirable and undesirable outputs means that proportional reductions of desirable and undesirable outputs are feasible. It allows for undesirable outputs to be deposed of at the same reduction cost as desirable outputs. Null-jointness of desirable and undesirable outputs implies that undesirable outputs are inescapable if desirable outputs are produced.

Given the production possibility set $P(x)$, a directional output distance function for the $i^{th}$ observation $(x_i, y_i, b_i)$ is defined as the simultaneous maximum reduction in undesirable outputs and expansion in desirable outputs along a direction $g = (g_y, g_b)$. Its mathematical form is:

$$D_i(x_i, y_i, b_i; g_y, g_b) = \max \{ \phi_i > 0 : (y_i + \phi_i g_y, b_i + \phi_i g_b) \in P(x_i) \}, \quad (2)$$

where $D_i$ is the distance function value for the $i^{th}$ observation $(x_i, y_i, b_i)$ given the directional vector $(g_y, g_b)$, and $\phi_i$ is the simultaneous change of desirable and undesirable outputs satisfying $(y_i + \phi_i g_y, b_i + \phi_i g_b) \in P(x_i)$.

The directional distance function is a measure of efficiency for the $i^{th}$ cropping system, representing the “distance” of the produced output bundle from the technically efficient production frontier along the directional vector $(g_y, g_b)$. The production frontier is constructed by a set of cropping systems, whose distance function equals zero, i.e. $D_i(x_i, y_i, b_i; g_y, g_b) = 0$. This means that there is no possibility for these systems to reduce undesirable outputs and expand desirable outputs; therefore they are called efficient technologies.
An input-output combination belonging to a production possibility set $P(x)$ can be represented by a directional output distance function equivalently, i.e. $(y_i, b_i) \in P(x)$ if and only if $D_i\left(x_i, y_i, b_i; g_y, g_b\right) \geq 0$. As shown in Figure 1, the dots represent a sample of all the observations that construct the production possibility set $P(x)$. The production possibility set is encompassed by the Pareto efficient frontier (i.e. the curve in Figure 1) and the horizontal axis. The observations beneath the frontier are inefficient and their distance functions are greater than zero (for example, the observation denoted by $(b, y)$). The observations on the frontier are efficient and their corresponding distance functions equal zero. The arrows denote the directional vector $(g_b, g_y)$, along which an inefficient observation can improve its efficiency by increasing desirable output and reducing undesirable output. For example, the efficiency of the observation $(b, y)$ can be improved by moving from $(b, y)$ to point E along the directional vector. The coordinate of point E is $(b + \varphi g_b, y + \varphi g_y)$. The relationship between the distance functions for point E and point $(b, y)$ can be illustrated by $D\left(x, y + \varphi g_y, b + \varphi g_b; g_y, g_b\right) = D\left(x, y, b; g_y, g_b\right) - \varphi$, which is also called translation property by Färe et al. (2005).

Figure 1. The Directional Output Distance Function

Corresponding to the assumptions imposed on the production possibility set, the directional output distance function has the following properties, which will be imposed as constraints when estimating the distance function.
1. \( D_i(x_i, y_i, b_i; g_y, g_b) \geq 0 \) if and only if \( (y_i, b_i) \) is an element of \( P(x) \).

2. \( D_i(x_i, y'_i, b_i; g_y, g_b) \geq D_i(x_i, y_i, b_i; g_y, g_b) \) for \( (y'_i, b_i) \leq (y_i, b_i) \).

3. \( D_i(x_i, y_i, b'_i; g_y, g_b) \geq D_i(x_i, y_i, b_i; g_y, g_b) \) for \( (y_i, b'_i) \geq (y_i, b_i) \).

4. \( D_i(x_i, \theta y_i, \theta b_i; g_y, g_b) \geq 0 \) for \( (y_i, b_i) \in P(x) \) and \( 0 \leq \theta \leq 1 \).

5. \( D(x, y, b; g_y, g_b) \) is concave if \( (y, b) \in P(x) \).

6. \( D_i(x_i, y_i + \varphi_i g_y, b_i + \varphi_i g_b; g_y, g_b) = D_i(x_i, y_i, b_i; g_y, g_b) - \varphi_i \).

2.2 Derivation of Shadow Prices

In order to derive the shadow prices, it is necessary to examine the relationship between the maximum revenue function and the directional distance function (Färe et al., 2006). Let \( p_y = (p_{y1}, \ldots, p_{yM}) \in \mathbb{R}^M_+ \) represent desirable output prices and let \( p_b = (p_{b1}, \ldots, p_{bJ}) \in \mathbb{R}^J_- \) represent the negative undesirable output prices. The revenue function, which considers the negative effect generated by the undesirable outputs, is defined as:

\[
R_i(x_i, p_y, p_b) = \max_{y, b} \{ p_y y_i + p_b b_i : (y, b) \in P(x) \}. 
\tag{3}
\]

The revenue function gives the maximal revenue that can be generated from inputs \( x \) under the technology constraint \( (y, b) \in P(x) \), when desirable output prices are \( p_y \) and undesirable output prices are \( p_b \). Since \( (y, b) \in P(x) \) implies \( D_i(x_i, y_i, b_i; g_y, g_b) \geq 0 \), the maximal revenue function can be equivalently written as:

\[
R_i(x_i, p_y, p_b) = \max_{y, b} \{ p_y y_i + p_b b_i : D_i(x_i, y_i, b_i; g_y, g_b) \geq 0 \}. 
\tag{4}
\]

To solve this equation, it is written as:

\[
R_i(x_i, p_y, p_b) \geq (p_y, p_b)(y + D_i(x_i, y_i, b_i; g_y, g_b)g_y, b + D_i(x_i, y_i, b_i; g_y, g_b)g_b)
\]

\[
= (p_y y + p_b b) + (p_y D_i(x, y, b; g)g_y + p_b D_i(x, y, b; g)g_b). 
\tag{5}
\]

Rearranging the above inequality, the directional distance function can be written as:

\[
D_i(x_i, y_i, b_i; g) \leq \frac{R_i(x_i, p_y, p_b) - (p_y y + p_b b)}{p_y g_y + p_b g_b}, 
\tag{6}
\]

which yields:
\[
D_i(x_i, y_i, b_i; g) = \min_p \left\{ \frac{R_i(x_i, y_i, b_i; p_y y_i + p_b b_i)}{p_y y_i + p_b b_i} \right\}.
\]

Applying the envelope theorem to equation (7) yielding:

\[
\nabla_b D_i(x_i, y_i, b_i; g) = \frac{-p_b}{p_y y_i + p_b b_i} \geq 0
\]

and

\[
\nabla_y D_i(x_i, y_i, b_i; g) = \frac{-p_y}{p_b b_i + p_{gb} b_i} \leq 0.
\]

Thus, given the m\(^{th}\) desirable output price, say \(p_{ym}\), the shadow price of the j\(^{th}\) undesirable output can be recovered by taking the ratio of Eq. (8) and Eq. (9):

\[
\frac{p_{bj}}{p_{ym}} = \frac{\partial D_i(x_i, y_i, b_i; g) / \partial b_j}{\partial D_i(x_i, y_i, b_i; g) / \partial y_m}
\]

or

\[
p_{bj} = p_{ym} \left( \frac{\partial D_i(x_i, y_i, b_i; g) / \partial b_j}{\partial D_i(x_i, y_i, b_i; g) / \partial y_m} \right).
\]

The previous equations depict a derivation of the shadow prices for the undesirable outputs. Equation (10) implies that revenue is maximized where the marginal rate of transformation between an undesirable output and a desirable output equals the price ratio of the two. The negative shadow prices of undesirable outputs, derived by a directional distance function, are interpreted as marginal opportunity costs in terms of foregone desirable outputs (Färe et al., 2006). The equations also provide an estimate of marginal abatement costs of agricultural pollutants to farmers.

**2.3 Estimation of Distance Function**

The previous section provides a conceptual way to estimate shadow prices of the undesirable outputs. Parameterizing the distance function is a necessary step in the model, since the derivatives of the distance function are utilized in equation 11. A linear programming technique is employed to calibrate the unknown parameters in the distance function. A regular
regression technique is not appropriate in this situation, because the values of the distance function would not be known until after the regression is estimated.

Among the flexible functional forms, a deterministic quadratic function is chosen to parameterize the directional distance function. A quadratic functional form can be restricted to satisfy the translation property (Färe et al., 2005) while a translog functional form, for example, cannot. Criterion for choosing the directional vector depends upon the technologies. The example in this paper uses \( g = (1, -1) \) as a direction vector, where the first \( M \) components equal 1 and the next \( J \) components equal -1. This means that the same proportion of reduction in undesirable outputs and expansion in desirable outputs will bring the inefficient observation to the efficient frontier. Assuming \( i = 1, \ldots, I \) cropping systems, the quadratic directional distance function for the \( i \)th cropping system is:

\[
D_i(x_i, y_i, b_i; 1, -1) = \alpha_0 + \sum_{n=1}^{N} \alpha_n x_{i,n} + \sum_{m=1}^{M} \beta_m y_{i,m} + \sum_{j=1}^{J} y_j b_{ij} \\
+ \frac{1}{2} \sum_{n=1}^{N} \sum_{n' = 1}^{N} \alpha_{nn'} x_{i,n} x_{i,n'} + \frac{1}{2} \sum_{m=1}^{M} \sum_{m' = 1}^{M} \beta_{mm'} y_{i,m} y_{i,m'} + \frac{1}{2} \sum_{j=1}^{J} \sum_{j' = 1}^{J} Y_{jj'} b_{ij} b_{ij'} + \sum_{n=1}^{N} \sum_{m=1}^{M} \delta_{nm} x_{i,n} y_{i,m} + \sum_{n=1}^{N} \sum_{j=1}^{J} \eta_{nj} x_{i,n} b_{ij} + \sum_{m=1}^{M} \sum_{j=1}^{J} \mu_{mj} y_{i,m} b_{ij} \tag{12}
\]

where \( D_i(x_i, y_i, b_i; 1, -1) \) is the value of distance function for the \( i \)th cropping system which use inputs \( x_i \) to produce outputs \( (y_i, b_i) \) given the directional vector \( (1, -1); \) \( x_{i,n} \) is the \( n \)th input of the \( i \)th cropping system, \( n = 1, \ldots, N; \) \( y_{i,m} \) is the \( m \)th desirable output of the \( i \)th cropping system, \( m = 1, \ldots, M; \) \( b_{ij} \) is the \( j \)th undesirable output of the \( i \)th cropping system, \( j = 1, \ldots, J; \) \( \Gamma = (\alpha_0, \alpha_n, \beta_m, \gamma_j, \alpha_{nn'}, \beta_{mm'}, \gamma_{jj'}, \delta_{nm}, \eta_{nj}, \mu_{mj}) \) is a vector of unknown parameters. Constraints on the parameters should be imposed to satisfy the properties of the distance function when estimating this quadratic function. Symmetry of the cross-output and cross-input effects is also assumed, and requires \( \alpha_{nn'} = \alpha_{n'n} \) for \( n \neq n'; \) \( \beta_{mm'} = \beta_{m'm} \) for \( m \neq m'; \) \( Y_{jj'} = Y_{j'j} \) for \( j \neq j'. \)

A linear programming technique is used to estimate the unknown parameters in the quadratic distance function following the work of Aigner and Chu (1968), which is also used by Färe et
Specifically, the parameters in equation 12 are estimated by minimizing the sum of the distances between the frontier technology and each individual observation, subject to the constraints implied by the distance function properties. This can be written into a linear programming form as follows:

$$\min_{\Gamma} \sum_{i=1}^{I} [D_i(x_i, y_i, b_i; 1, -1) - 0]$$

subject to:

$$D_i(x_i, y_i, b_i; 1, -1) \geq 0, i = 1, ..., I$$ (13a)

$$\frac{\partial D_i(x_i, y_i, b_i; 1, -1)}{\partial b_j} \geq 0, i = 1, ..., I, j = 1, ..., J$$ (13b)

$$\frac{\partial D_i(x_i, y_i, b_i; 1, -1)}{\partial y_m} \leq 0, i = 1, ..., I, m = 1, ..., M$$ (13c)

$$\frac{\partial D_i(x_i, y_i, b_i; 1, -1)}{\partial x_n} \geq 0, i = 1, ..., I, n = 1, ..., N$$ (13d)

$$\sum_{m=1}^{M} \beta_m - \sum_{j=1}^{J} \gamma_j = -1, \sum_{m'=1}^{M} \beta_{mm'} - \sum_{j=1}^{J} \mu_{mj} = 0, m = 1, ..., M$$ (13e)

$$\sum_{j'=1}^{J} \gamma_{jj'} - \sum_{m=1}^{M} \mu_{mj} = 0, j = 1, ..., J$$ (13f)

$$\sum_{m=1}^{M} \delta_{nm} - \sum_{j=1}^{J} \eta_{nj} = 0, n = 1, ..., N$$ (13g)

$$\alpha_{nn'} = \alpha_{n'n} \text{ for } n \neq n'; \beta_{mm'} = \beta_{m'm} \text{ for } m \neq m'; \gamma_{jj'} \neq \gamma_{j'j} \text{ for } j \neq j'.$$ (13h)

where $\Gamma$ is a vector of the unknown parameters in equation 12.

### 3. Data

We consider the case of one desirable output, maize yield, one undesirable output, CO2 emissions from burning maize straw, and one input, total cost, which summarizes labor, machinery and materials costs. Our data is provincial level yearly panel data that covers seven major maize provinces in China, including Anhui, Hebei, Henan and Shandong in North China Plain and Heilongjiang, Jilin and Liaoning in Northeast China from 1996 to 2013.

To eliminate the influence of inflation, we deflate grain price and total cost to the 2010 price.
Price index is from China Statistical Yearbook. Maize yield in measured in kg/ha. Total cost is measured in yuan/ha. Both Maize yield and total costs are from The Compiled Materials of Costs and Profits of Agricultural Products of China, 1996-2013, published by the State Development and Planning Commission. CO2 emissions is measured in kg/ha and calculated by the following formula:

$$\text{CO2} = Y \cdot R \cdot B \cdot CF \cdot EF,$$

Where the variables are described in Table 1.

Maize straw is estimated by multiplying crop yield (Y) and residue to crop ratio (R). We assign the median of R (1.25) from several literatures. The percentage of burnt biomass is key to calculating CO2 emissions from burning crop residues. We surveyed 7-14 village leaders randomly in each province to estimate the utilization of maize straw in percentage in their villages in 2015, 5 years ago (2010), 10 years ago (2005) and 15 years ago (2000). Then we expand the survey data to other years from 1996 to 2013 by assuming the change rate is the same between years during every 5 years. The amount of burnt biomass is calculated by multiplying the amount of biomass with the burnt percentage. We also multiply a combustion factor, which is the fraction of the mass combusted during the course of a fire. Finally, an emission factor (g/kg), estimated by Streets et al., (2003); Turn (2007), is used to calculate CO2 emissions. The emission factor (g/kg), is the amount of CO2 in g emitted by burning 1 kg maize straw.

The utilization of maize straw differs largely across provinces (Figure 2). Three major utilization types include open field burning, livestock feed and biomass residue. Livestock production has been specialized and separated from grain production over the past decade, so the crop residue used to feed animals has been replaced by other materials such as maize. Nearly 1/3 of maize straw were used to feed animals in the seven provinces in 1996, while it decreased to 7% in 2013. As soil conservation technology, including returning residue to field, has been promoted by the government, increasingly more crop residue has been returned to field to keep nutrients in the soil. However, the practice of returning crop residue to the field is less common in Northeast China than North China Plain, since crop residue is hard to decay due to
the cold weather in Northeast China. In North China Plain, the practice of returning maize straw to the field increased from less than 2% in 1996 to around 37% in 2013. In contrast, Northeast China started returning maize straw to field beginning in 2006, but the practice did not expand at the same rate. On average, only less than 1% of maize straw was returned in 2006, though in 2013, only around 7% was returned to field. Burning crop residue is a labor saving method to clear up the field for next crop season. A likely explanation for the difference is that youth have migrated to cities, which has affected the labor force, and hence, agricultural production practices. In many rural areas the labor tends to be older, so farmers tend to be more inclined to burn crop residues in open field, especially in Northeast China. Around 60% of crop residues were burnt from 1996 to 2013 in North China Plain, while nearly 85% of maize straw were burnt over the same period in Northeast China.

Table 1. Description of key variables in the estimation of CO2 emissions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Data range</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>Maize yield (kg/ha)</td>
<td>1890-8211</td>
<td>The Compiled Materials of Costs and Profits of Agricultural Products of China, 1996-2013, published by the State Development and Planning Commission</td>
</tr>
<tr>
<td>R</td>
<td>Residue to crop ratio</td>
<td>1.25</td>
<td>Median from the following literature: Yukihiko Tsumura et al. (2005); Liu et al. (2008); Kim and Dale (2004); Zeng et al. (2007); Lal (2005); Shen et al. (2010); Cui et al. (2008); Song (2010); Jia (2006); Bi (2010); Ministry of Science and Technology (1999); Renewable Energy Project (2008)</td>
</tr>
<tr>
<td>B</td>
<td>Percentage of burnt crop residue (%)</td>
<td>39-89</td>
<td>Surveys on village leaders by the authors</td>
</tr>
<tr>
<td>CF</td>
<td>Combustion factor, which is the fraction of the mass combusted during the course of a fire</td>
<td>0.92</td>
<td>Streets et al., (2003); Turn (2007)-WLL</td>
</tr>
<tr>
<td>EF</td>
<td>Emission factor (g/kg), which is the amount of CO2 in g emitted by burning 1 kg maize straw</td>
<td>1350</td>
<td>Streets et al., (2003); Turn (2007)-WLL</td>
</tr>
</tbody>
</table>
Figure 2. Utilization of crop residue by province, 1996-2013 (%)

The summary statistics of the key variables are presented in Table 2. The trends of the three key variables are presented in Figure 3.

Table 2. Summary statistics for inputs and outputs in maize production, 1996-2013 (price in
### 2010 Year

<table>
<thead>
<tr>
<th>Region</th>
<th>Input: total cost (yuan/ha)</th>
<th>Desirable Output: maize yield (kg/ha)</th>
<th>Undesirable CO2 emission (kg/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
</tr>
<tr>
<td>All seven provinces</td>
<td>5328</td>
<td>1683</td>
<td>6141</td>
</tr>
<tr>
<td>Anhui</td>
<td>4834</td>
<td>1707</td>
<td>5272</td>
</tr>
<tr>
<td>Hebei</td>
<td>5241</td>
<td>1513</td>
<td>6133</td>
</tr>
<tr>
<td>Heilongjiang</td>
<td>4235</td>
<td>1044</td>
<td>6069</td>
</tr>
<tr>
<td>Henan</td>
<td>5064</td>
<td>1694</td>
<td>5761</td>
</tr>
<tr>
<td>Jilin</td>
<td>6197</td>
<td>1656</td>
<td>6930</td>
</tr>
<tr>
<td>Liaoning</td>
<td>5717</td>
<td>1661</td>
<td>6346</td>
</tr>
<tr>
<td>Shandong</td>
<td>6005</td>
<td>1767</td>
<td>6477</td>
</tr>
</tbody>
</table>
4. Results

To avoid the convergence problem, we normalized the data by dividing each output and each input by their respective mean values (Färe et al. 2005).

The parameters estimated for the translog functional form of the directional distance function (12) are obtained by solving the linear programming (13) using MATLAB. The estimated parameters are reported in Appendix Table 1. Once the parameters are obtained, we are able to calculate the directional output distance functions for each province in each year by inserting the estimated parameters back into Eq. (12). The directional output distance function serves as a measure of technical inefficiency. It gives the maximum unit expansion of the good output and contraction of the bad output. If the directional distance function equals zero, then we say that the production is fully efficient. A positive score means the presence of inefficiency in the production process. A higher score of the directional distance function means a higher technical inefficiency.
We calculate the technical efficiency by using one minus the distance function value. Efficiency score for North China Plain and Northeast China are plotted in Figure 4 and 5. It shows a decreasing trend in Anhui and Shandong province, while it increases in Hebei and Henan. One reason is that open field burning in Hebei and Henan decreases substantially due to increased amount returned to field. There are some fluctuations with no clear trend in the provinces of Northeast China.

We further analyze the factors that contribute to the efficiency score by regressing input, desirable output, and undesirable output on the efficiency score. We use the natural log form of each variable. The results are shown in Table 3. It shows that an increase in maize yield by 1% will lead to an increase in efficiency by 0.3%. A decrease in total cost by 1% will lead to increase in efficiency by 0.1%. A decrease in burnt maize straw by 1% will lead to an increase in efficiency by 0.2%. The fluctuations of efficiency scores over time result from the mixed changes of input, desirable output and undesirable output.

Figure 4. Efficiency Score in North China Plain, 1996-2013
Table 3. Regression results on the factors affecting efficiency score

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Coefficients</th>
<th>Standard errors in parentheses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln(yield)</td>
<td>0.335***</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Ln(total cost)</td>
<td>-0.133***</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Ln(burnt percent)</td>
<td>-0.232***</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.943***</td>
<td>(0.257)</td>
</tr>
<tr>
<td>Observations</td>
<td>126</td>
<td></td>
</tr>
<tr>
<td>Number of provinces</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>Within R-sq</td>
<td>0.636</td>
<td></td>
</tr>
<tr>
<td>Between R-sq</td>
<td>0.929</td>
<td></td>
</tr>
<tr>
<td>Overall R-sq</td>
<td>0.740</td>
<td></td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.1

Figure 6 plots the kernel densities of the shadow prices for Northeast China and North China.
Plain. On average, the shadow price of CO2 in Northeast China is 0.342 yuan/kg, which is cheaper than that in North China Plain (0.611). It implies that if policy makers better to start the abatement of CO2 emissions from Northeast China until the shadow prices of CO2 is equal or larger than that in North China Plain. The summary of descriptive statistics of CO2 shadow price by province is shown in Table 4. Figure 7 shows that the shadow price of CO2 at national level is decreasing over time. It implies that as emissions increase, marginal cost of abating CO2 is lower.

Table 4. Summary of descriptive statistics of CO2 shadow price by province, 1996-2013 (yuan/kg)

<table>
<thead>
<tr>
<th>Province</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nation</td>
<td>0.496</td>
<td>0.112</td>
<td>0.259</td>
<td>0.699</td>
</tr>
<tr>
<td>Northeast China</td>
<td>0.342</td>
<td>0.145</td>
<td>0</td>
<td>0.686</td>
</tr>
<tr>
<td>Heilongjiang</td>
<td>0.398</td>
<td>0.087</td>
<td>0.285</td>
<td>0.555</td>
</tr>
<tr>
<td>Jilin</td>
<td>0.228</td>
<td>0.130</td>
<td>0.000</td>
<td>0.529</td>
</tr>
<tr>
<td>Liaoning</td>
<td>0.399</td>
<td>0.143</td>
<td>0.138</td>
<td>0.686</td>
</tr>
<tr>
<td>North China Plain</td>
<td>0.611</td>
<td>0.178</td>
<td>0.240</td>
<td>1.368</td>
</tr>
<tr>
<td>Anhui</td>
<td>0.664</td>
<td>0.275</td>
<td>0.257</td>
<td>1.368</td>
</tr>
<tr>
<td>Hebei</td>
<td>0.618</td>
<td>0.101</td>
<td>0.466</td>
<td>0.816</td>
</tr>
<tr>
<td>Henan</td>
<td>0.635</td>
<td>0.122</td>
<td>0.399</td>
<td>0.911</td>
</tr>
<tr>
<td>Shandong</td>
<td>0.529</td>
<td>0.143</td>
<td>0.240</td>
<td>0.824</td>
</tr>
</tbody>
</table>
Figure 6. Kernel density estimate of CO2 shadow price in Northeast China and North China Plain.

Figure 7. Shadow price of CO2 at national level from 1996 to 2013.
Figure 8. Shadow price of CO$_2$ vs. CO$_2$ emissions

Figure 8 shows that the larger amount of CO$_2$ emissions, the lower shadow prices. It implies that given current technology, CO$_2$ abatement should start from the place where CO$_2$ are higher. By regression natural log of shadow price on the amount of CO$_2$ emissions, we obtained the elasticity is -1.33. It implies that an increase in CO$_2$ emissions by 1% will lead to a decrease of CO$_2$ emission by 1.33%.

We further assumes that maize yield decreases by 10% and maize straw decreases by 50% under conservation practices (scenario1). We want to compare the efficiency impact from the conservation practices as well as the differences in the abatement costs between conventional practices and conservation practices. Figure 9 shows that the average efficiency increases by 9% from 0.812 under baseline to 0.886 under scenario 1. Under baseline, if CO$_2$ emissions are abated by 50% by reducing maize production, the abatement cost is 1032 yuan/ha (Figure 10). Under scenario 1, the abatement cost of reducing CO$_2$ emission by 50% is equal to 10% of the maize revenue (831 yuan/ha). The difference of abatement cost (201 yuan/ha) provides a reference for policy makers to subsidize farmers to adopt conservation practices. The whole
society will benefit if the government spend less than 201 yuan/ha to promote adoption of conservation practices. The does not take other negative effects of CO\textsubscript{2} emissions into account, such as delays of airlines, trouble in ground transportation, and human health, etc. Du et al. (2015) estimates the marginal abatement cost curve of CO\textsubscript{2} emissions in China based on a provincial panel for the period of 2001-2010. Their estimates show that China would incur 559-623 yuan/t (roughly 51-57\%) increase in marginal abatement cost to achieve a corresponding 40-45\% reduction in carbon intensity compared to its 2005 level.

![Kernel density estimate](image)

Figure 9. Kernel density estimate of efficiency under current practices vs. conservation practices
5. Discussion and conclusions

The reduction of CO\textsubscript{2} emissions in agricultural sector is a key step to cope with the social costs of climate change. As the largest agricultural GHGs emitter, China’s agricultural sector has been attracting increasing attention, although this study also contributes to the emerging literature on abatement costs of agricultural emissions. In order to estimate the cost-effectiveness of allocating carbon reduction among different sectors or different sub-sectors within agriculture, a necessary first step is to analyze the marginal abatement cost of CO\textsubscript{2}.

This paper estimated CO\textsubscript{2} shadow prices from burning crop residue as well as the production efficiency with consideration of CO\textsubscript{2} emissions as undesirable outputs. The environmental production efficiency varies in different provinces and years. Regression analysis shows that an increase in maize yield by 1% will lead to an increase in efficiency by 0.3%. A decrease in total cost by 1% will lead to increase in efficiency by 0.1%. A decrease in burnt maize straw by 1% will lead to an increase in efficiency by 0.2%. The fluctuations of efficiency scores over time result from the mixed changes of input, desirable output and undesirable output.

Figure 10. Kernel density estimate of abatement cost under current practices vs. conservation practices
The shadow price of CO$_2$ from burning crop residue is estimated to range from 0-1.368 yuan/ha (or US$210.5/t) with an average of 0.496yuan/kg (or US$76/t). Table 5 compares our results with other studies. There is a wide range of shadow prices of CO$_2$ depending on the study period, sector, sample and model.

Table 5. Comparison with previous studies

<table>
<thead>
<tr>
<th>Study</th>
<th>Period</th>
<th>Sector</th>
<th>Sample</th>
<th>Model</th>
<th>Mean value ($/t) $^3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wang et al. (2011)</td>
<td>2007</td>
<td>Economy</td>
<td>30 Provinces in China</td>
<td>DEA</td>
<td>62.5</td>
</tr>
<tr>
<td>Du et al. (2015)</td>
<td>2001-2010</td>
<td>Economy</td>
<td>30 Provinces in China</td>
<td>DDF+LP</td>
<td>120-310</td>
</tr>
<tr>
<td>Wei et al. (2013)</td>
<td>2004</td>
<td>Energy</td>
<td>124 Power plants in China</td>
<td>DDF+LP, DDF+ML</td>
<td>248.2, 73.8</td>
</tr>
<tr>
<td>Tang et al. (2016)</td>
<td>1998-2005</td>
<td>Agriculture</td>
<td>29 farms in Australia</td>
<td>DF+LP</td>
<td>29.3</td>
</tr>
<tr>
<td>Thamo et al. (2013)</td>
<td>Simulation data</td>
<td>Agriculture</td>
<td>Farms in Western Australia</td>
<td>MIDAS$^4$</td>
<td>50</td>
</tr>
<tr>
<td>Flugge and Abadi (2006)</td>
<td>Simulation data</td>
<td>Agriculture</td>
<td>Two regions in Western Australia</td>
<td>MIDAS</td>
<td>55</td>
</tr>
<tr>
<td>This study</td>
<td>1996-2013</td>
<td>Agriculture</td>
<td>7 provinces in China</td>
<td>DDF+LP</td>
<td>76</td>
</tr>
</tbody>
</table>

$^1$Adapted from Du et al.(2005)

$^2$SDF, DDF, LP, ML, DEA denote Shephard Distance Function, Directional Distance Function, Linear Pro-ta Envelopment Analysis, respectively

$^3$All the shadow prices are transformed into US dollars according to the corresponding exchange rate for the convenience of comparison

$^4$A steady-state optimization farm model

The shadow price of CO$_2$ has an inverse relationship with the amount of emissions. The elasticity is 1.33, which means an increase in CO2 emissions by 1% will lead to a decrease of CO2 emission by 1.33%.

The average efficiency increases by 9% from 0.812 under baseline to 0.886 under scenario 1 (adoption conservation practices with 10% decrease in yield and 50% decrease in burnt crop.
residue). The shadow prices in these two cases imply that the whole society will benefit if the government spend less than 201 yuan/ha to promote adoption of conservation practices.

Several parametric issues are available for discussion. The first matter involves how to choose directional vector. In this paper, we use $g=(1,1)$, which means desirable output decreases by 1 unit, undesirable output also decreases by 1 unit. In many of the studies presented in Table 5, $g=(1,1)$ is assumed. It is important to reflect upon whether we use empirical relationship to inform the choice of directional vector, and how whether the directional vector affects the result. In order to explore this, further sensitivity analysis is required. A second parametric issue is that when we include other crops, should we analyze all crops together or analyze it by crop? Analyzing all crops together assumes that there is substitutability between crops, while analyzing these separately assumes that there is an impossibility of changing from planting one crop to another. Another line of inquiry would explore why the results are so sensitive as indicated by the literature.

There are several practical policy implications arising from this study. One area that merits additional exploration is the trade-off between reduced yields and practices that substantially decrease CO2 emissions. Decreasing CO2 emissions provides marginal social benefits that may conflict with societal food security goals and individual farmer production. Clearly, the results from this model show that there are not incentives for farmers to implement production practices that decrease yield and presumably, profits. Thus, it would be paramount for the government’s willingness to compensate farmers to implement conservation practices that will reduce CO2 emissions. However, the implications of reduced agricultural yields may be juxtaposed with other dietary and nutritional goals that otherwise enhance food security. Furthermore, there may be differences between the regions that warrant additional consideration, and as a result, the regions might not be managed uniformly. In summary, this preliminary analysis provides guidance about environmental and agricultural targets that require more extensive research, and that may have implications at many tiers, extending from the level of the farm to the international scale.
Reference:


Greenhouse gas emissions, especially CO2, from burning crop residues in China has been paid attentions scholars.


Appendix

Appendix Table 1. Estimated Coefficients in the Quadratic Distance Function

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_0$</td>
<td>Intercept</td>
<td>-0.129</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>$x$: total cost (yuan/ha)</td>
<td>0.543</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>$y$: crop yield (kg/ha)</td>
<td>-0.339</td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>$b$: CO2 emissions (kg/ha)</td>
<td>0.661</td>
</tr>
<tr>
<td>$\alpha_{11}$</td>
<td>$1/2x^2$: half of squared total cost</td>
<td>-0.083</td>
</tr>
<tr>
<td>$\beta_{11}$</td>
<td>$1/2y^2$: half of squared crop yield</td>
<td>-0.140</td>
</tr>
<tr>
<td>$\gamma_{11}$</td>
<td>$1/2b^2$: half of squared CO2 emissions</td>
<td>-0.140</td>
</tr>
<tr>
<td>$\delta$</td>
<td>$xy$: cross term of total cost and crop yield</td>
<td>-0.131</td>
</tr>
<tr>
<td>$\eta$</td>
<td>$xb$: cross term of total cost and CO2 emissions</td>
<td>-0.131</td>
</tr>
<tr>
<td>$\mu$</td>
<td>$yb$: cross term of crop yield and CO2 emissions</td>
<td>-0.140</td>
</tr>
</tbody>
</table>

1 The maximal revenue must be associated with the cropping systems after their inefficiencies are eliminated.