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A nonparametric method to estimate a technical change effect on marginal abatement costs of U.S. coal power plants

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ABSTRACT

The literature usually assumes that technical change reduces marginal abatement cost; however, recent results suggest that precisely the opposite occurs. This paper proposes a nonparametric method to determine the effect of technical change on marginal abatement cost. The method decomposes NO_x marginal abatement cost changes in 2000–2004 and in 2004–2008 for 325 boilers operating in 134 U.S. bituminous coal power plant into technical and non-technical change effects. We find that technical change reduces the NO_x marginal cost about 28.3% in 2000–2004 and 26.5% in 2004–2008. However, more stringent regulations enacted the NO_x budget program results in lower NO_x emission levels as plant operators install more advanced NO_x abatement equipment which in turn causes an overall increase in marginal abatement cost.

1. Introduction

The relationship between innovation and environmental policy has received considerable attention in recent years in part because the Porter hypothesis (Porter and van der Linde, 1995) suggested that more stringent environmental policy could provide incentives for firms to develop new pollution controls that could also augment general productivity. The enactment of the 1990 Clean Air Act (CAA) resulted in environmental programs and regulations that are designed to reduce nitrogen oxides (NO_x), the key pollutant in ground level ozone and acid rain. Coal power plants are the primary generators of NO_x. From 2000 to 2008, eastern U.S. coal power plants operating under the Ozone Transport Commission's (OTC) NO_x budget program and the NO_x budget trading program significantly lowered their NO_x emission to meet the regulated reduction targets. As reported in EPA (2009), the average regional ozone season NO_x emission[1] from affected coal, oil, and gas power plants decreased from 1256 thousand tons in 2000, to 849 thousand tons in 2003, and 481 thousand tons in 2008. For affected coal power plants, the average regional ozone season NO_x emission decreased from 800 thousand tons in 2003 to 456 thousand tons in 2008, while the average levels of heat input were relatively stable between 4.91 and 5.15 billion mmBtu. Furthermore, the average emission rate was reduced from 0.32 lb/mmBtu in 2003 to 0.18 lb/mmBtu in 2008. One reason for the dramatic decrease is believed to be the adoption of NO_x abatement technologies such as low NO_x burners, overfire air, selective catalytic reduction and selective non-catalytic reduction (EPA, 2009). However, the average NO_x emission rate for regulated plants that did not install additional equipment also decreased from about 0.55 lb/mmBtu in 2003 to about 0.32 lb/mmBtu in 2008. We investigate the cost motivations for these changes in pollution rates.

The marginal abatement cost curve (MACC) is a standard analytical tool in environmental economics (Klepper and Petersen, 2006; Vijay et al., 2010) that links firms' emission levels to an additional cost of reducing a unit of pollution emission, or marginal abatement cost (MAC). Firms' MAC provides valuable information for determining pollution taxes, setting the level of emission permits, and estimating prices of pollutants in allowance markets. As stated in EPA (2009), NO_x allowance prices should reflect firms' specific NO_x MAC; thus, a variety of emission control decisions can be made based on the firms' NO_x MAC.

Technical change can result in either reduced or increased MAC. In general, a number of theoretical models simply assume that technical change directly lowers MAC at all abatement levels (Milliman and Prince, 1989; Rosendahl, 2004; Bramoulle and Olson, 2005; Fisher et al., 2003). However, Baker et al. (2008) reviewed several theoretical models and concluded that different approaches to derive MAC and

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[1] Regional ozone season NO_x emission is the level of NO_x emission between May 1 and September 30 in twenty affected eastern states.

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model technical change can produce different conclusions. One example considers a nested CES production function and technical change represented by a knowledge parameter. When knowledge can substitute for both fossil and non-fossil energy inputs, MAC must be lowered by technical change; however, when knowledge can substitute for only fossil energy, MAC increases with technical change at higher levels of abatement. Baker et al. (2006) provide another example in which technical change is modeled by an R&D parameter. MAC is lower when R&D leads to a uniform quantity reduction in emissions and higher when R&D causes proportional emission reduction. Baker et al. (2006) give no-cost sequestration program for fossil-fuel electricity generation and combined cycle gasification for electric generation as examples of uniform quantity reduction and proportional emission reduction, respectively. In conclusion, technical change does not necessarily imply a reduction in MAC. However, several of the models explored in Baker et al. (2008) have strong parametric or substitution assumptions. Thus the motivation for this paper is to develop nonparametric tools for estimating the empirical impact of technical change on MAC.

Technical change is viewed as a shift of the production frontier over time. The most common method of representing technical change in existing economic studies is to assume Hicks neutral technical change (Hicks, 1966), Solow neutral technical change (Solow, 1956, 1957) or biased technical change through coefficients within particular parametric production functions. In the nonparametric frontier literature, the production frontier is constructed contemporaneously or sequentially (Tulkens and Van den Eeckaut, 1995). Contemporaneous production frontiers are those in which each time period's production frontier is estimated independently using only corresponding time period observations. Using them allows technological regress, meaning that production frontiers can move inward from previous periods. Sequential production frontiers use all observations from past periods up to the current period and ensure that the estimated production frontier envelops the previous period's frontier, meaning that only technological progress exists, Diewert (1980).

To measure the effect of technical change, researchers apply index numbers and decomposition methods to derive meaningful components including technical change. One example of this approach is the construction of the Malmquist productivity index. Färe et al. (1994) construct contemporaneous production frontiers and estimate a set of distance functions to derive the Malmquist productivity index and its components. The estimated Malmquist productivity index is decomposed into an efficiency change effect, an activity effect, and a technical change effect; Färe et al. apply this technique to the productivity growth in OECD countries. Alternative Malmquist productivity index decompositions include Ray and Desli (1997) and Balk (2001). Shestalova (2003), who argues that technological regress does not exist in the manufacturing industry, decomposes the Malmquist productivity index based on a sequential production frontier to evaluate productivity change in manufacturing in OECD countries. Grifell-Tatje and Lovell (1999) decompose the profit change of Spanish banks into productivity, activity, and price effects; a technical change effect is included in the productivity effect and each term in profit decomposition is computed by the distance functions calculated using the sequential frontiers method.

The objective of this paper is to measure the effect of technical change on NO_x MAC of U.S. coal power plants in 2000–2008. During this period, coal power plants significantly reduced their NO_x emission levels. We investigate if these results derive from normal replacement of equipment, or from innovation perhaps induced from more stringent NO_x regulation programs. To measure the innovation effect on NO_x MAC, we develop a two-stage decomposition method for the MAC change index. The first stage decomposes the MAC change index into a technical change effect and a non-technical change effect. The second stage decomposes the non-technical change effect into a pollutant level effect, production input scale effect, and abatement input cost effect. To empirically implement the MAC change index decomposition, we develop a three-step estimation method. The first step estimates multiple-period sequential pollutant frontiers.[2] As reported in EPA (2009), the NO_x emissions per heat inputs from U.S. coal power plants have decreased consistently since 2000. This motivates us to use sequential pollutant frontiers to analyze the innovation effect.[3] While the method to nonparametrically estimate sequential production frontiers for the deterministic case already exists by using sequential Data Envelopment Analysis (DEA)[4], there is no method that can estimate sequential production frontiers in stochastic cases. This paper introduces a modified version of the Convex Nonparametric Least Square (CNLS)[5] program that can estimate multiple-period sequential production frontiers when noise is considered. The second step recovers unobserved abatement cost minimization points on the estimated pollutant frontiers by solving several linear programming problems. The third step calculates a technical change effect and a non-technical change effect of MAC decomposition.

Other researchers have used alternative methods and models to investigate U.S. coal power plants with a slightly different focus. For example, Pasurka (2006) looks at the relationship between emission levels and technical efficiency, technical change, growth in fuel and non-fuel inputs, and changes in the mix of good and bad output. Färe et al. (2006) develop an environmental performance index (EPI) to evaluate coal power plants. Their analysis indicates that plants participating in Phase I of the Acid Rain Program perform significantly better in terms of the EPI. Färe et al. (2010) extend the EPI to consider multiple pollutants and use the index to investigate 96 coal power plants between 1998–2005. Färe et al. (2007) investigate the counter factual, what if bad output is not regulated, and conclude measures such as productivity and technical change associated with abatement activity decline, but the change is not statistically significant. Färe et al. (2014) identify the potential gains from tradable permits using a deterministic DEA type model. While Färe et al. (2005) investigates power plants chose to focus on a parametric deterministic model to describe features of the technology such as substitutability between good and bad outputs and shadow prices of pollutants. The focus of our analysis differs in that we are primarily interested in the effect of technical change on MAC and we use data on U.S. coal power plants from 2000, 2004, and 2008 to investigate this relationship. Our model is axiomatic like the DEA type models used in the research mentioned above; however, our model is distinguished from other models by allowing for both inefficiency and noise in the deviations from the estimated function.

This paper is organized as follows. Section 2 describes the model and has two subsections: Section 2.1 gives a brief review of theoretical framework of the pollutant frontier and its relationship to MAC and Section 2.2 describes the decomposition of the MAC change index. The three-step estimation procedure is described in Sections 3.1, 3.2, and 3.3. The data set describing the electricity generating resources, emissions, and abatement inputs is described in Section 4. Section 5 presents and discusses the empirical results and Section 6 gives conclusions.An on-line appendix provides additional details regarding Malmquist calculations, the algorithm to calculate the sequential set of frontiers, linear programs to calculate the necessary abatement cost minimizing points, and the construction of abatement inputs and associated unit costs.

[2] Pollutant frontier is a function that describes a minimum level of pollutants given levels of production inputs and abatement inputs. More detail appear in Section 2.1.

[3] If the decrease in emission is coming solely from additional abatement efforts, rather than technical progress, we would expect to estimate zero technical progress.

[4] Kuosmanen and Johnson (2010) showed the relationship between the deterministic DEA estimator and CNLS.

[5] For introductory material on CNLS see for example Kuosmanen et al. (2014) or Johnson and Kuosmanen (2014).

2. Model

2.1. Using a pollutant function frontier to minimize abatement cost and to estimate marginal abatement cost

This section briefly reviews the concept of a pollutant function frontier and its connection to MAC and abatement cost functions introduced in Mekaroonreung and Johnson (2012). Let b be a pollutant produced by the use of a vector of production inputs $\boldsymbol{x}_p \in R_+^M$ where M is the number of production inputs and abated by the use of a vector of abatement inputs $\boldsymbol{x}_a \in R_+^Q$ where Q is the number of abatement inputs. Let $\boldsymbol{o} \in R_+^w$ be a vector of other variables characterizing the production conditions where w is the number of variables. The level of pollutant b can be written as a function of production inputs, abatement inputs, and production conditions, $b = B(\boldsymbol{x}_p, \boldsymbol{x}_a; \boldsymbol{o})$. Call $B()$ as the pollutant function. It has been shown in Mekaroonreung and Johnson (2012) that the pollutant function satisfies three properties:

1.) increasing in production inputs with increasing rate ($\frac{\partial B}{\partial x_{p_m}} \geq 0$ and $\frac{\partial^2 B}{\partial {x_{p_m}}^2} \geq 0$),
2.) decreasing in abatement inputs with decreasing rate ($\frac{\partial B}{\partial x_{a_q}} \leq 0$ and $\frac{\partial^2 B}{\partial {x_{a_q}}^2} \geq 0$), and
3.) convex in $\boldsymbol{x}_p$ and $\boldsymbol{x}_a$.

The signs on the derivatives are a direct result of the standard production axioms and weak disposability between good and bad outputs as described in Shephard (1970). More specifically, the first condition bad output is increasing in production inputs with an increasing rate. This assures a monotonic relationship between production inputs and bad output. The second condition states that bad output is decreasing in abatement inputs with a decreasing rate. This assures that the use of abatement inputs decreases bad output; however additional units of abatement inputs are less effective. Finally the third condition imposes convex input sets and convex abatement input sets. This assures that using a mixture of production inputs leads to improved productivity in terms of bad outputs and that using a mixture of abatement inputs to reduce bad outputs is more effective than specializing using a single abatement input.

Assume that a firm optimizes the use of abatement inputs to ensure that a given level of pollutant[6] is not exceeded and a fixed level of output is produced using a given level of production inputs. The abatement cost function can be written as $C(\boldsymbol{w}_{x_a}, \boldsymbol{x}_p, b) = \min x_a\{\boldsymbol{w}_{x_a}{}'\boldsymbol{x}_a : B(\boldsymbol{x}_a; \boldsymbol{x}_p, o) \leq b\}$ where $\boldsymbol{w}_{x_a} \in R_+^Q$ are the unit costs of abatement inputs.[7] From this abatement cost function, MAC can be calculated as the shadow price of the pollutant function constraint, specifically:

$$\text{MAC of a pollutant } b = -\frac{w_{x_{a_q}}}{\dfrac{\partial B}{\partial x_{a_q}}} \qquad \forall q = 1, \ldots, Q. \tag{1}$$

When MAC is calculated in two adjacent periods, the method described below is used to decompose the ratio of MAC^t and MAC^{t+1}.

2.2. Marginal abatement cost decomposition

Our strategy to decompose the MAC ratio $\frac{\text{MAC}^{t+1}}{\text{MAC}^t}$ in multiple stages is similar to the method of Grifell-Tatje and Lovell (1999). In the first stage, the MAC ratio is decomposed into a technical change effect and a non-technical change effect. In the second stage, the non-technical change effect is a production input scale effect, and an abatement input cost effect.

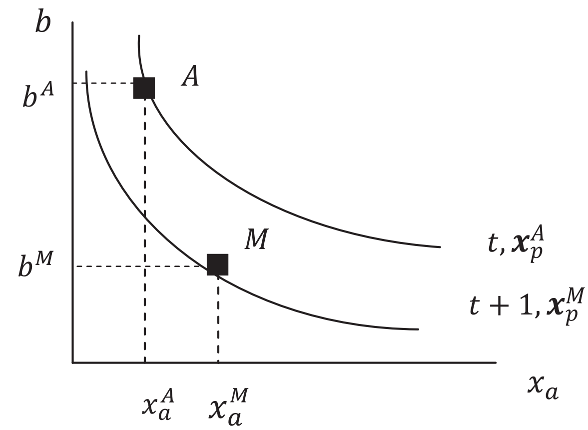

Fig. 1. Technical progress exists from period t to period $t + 1$.
Note that Fig. 1 is drawn to show the curvature of the pollutant frontiers. When estimated, the pollutant frontier can intersect either or both the bad output or abatement input axis.

Fig. 1 shows an example in which innovative activities have taken place. Technical progress is observed and the pollutant frontier shifts down from period t to $t + 1$. Assume at time t that a firm operates at point A with $(\boldsymbol{x}_a^A, \boldsymbol{x}_p^A, b^A)$ and at time $t + 1$, it operates at point M with $(\boldsymbol{x}_a^M, \boldsymbol{x}_p^M, b^M)$.

Two factors affect changes in abatement inputs from period t to $t + 1$. We identify: 1) a technical change effect and 2) a non-technical change effect. A technical change effect changes the use of abatement inputs due to a shift in the pollutant frontier holding other factors fixed. A non-technical change effect causes changes in the level of abatement inputs due to the firm's adjustments in the same period.

To quantify the change in MAC between a period t pollutant frontier and a period $t + 1$ pollutant frontier, we use the ratio $\frac{MAC^{t+1}}{MAC^t}$:

$$\frac{\text{MAC}^{t+1}}{\text{MAC}^t} = \left(\frac{w_{x_{a_q}}^{t+1}}{w_{x_{a_q}}^t}\right)\left(\frac{\dfrac{\partial B^t\left(\boldsymbol{x}_a^A; \boldsymbol{x}_p^A, b^A\right)}{\partial x_{a_q}}}{\dfrac{\partial B^{t+1}\left(\boldsymbol{x}_a^M; \boldsymbol{x}_p^M, b^M\right)}{\partial x_{a_q}}}\right). \tag{2}$$
[8]

The MAC ratio (2) can be multiplicatively decomposed into a technical change effect and a non-technical change effect using period $t + 1$ technology as[9]:

$$\frac{\text{MAC}^{t+1}}{\text{MAC}^t} = \underbrace{\left(\frac{\dfrac{\partial B^t\left(\boldsymbol{x}_a^A; \boldsymbol{x}_p^A, b^A\right)}{\partial x_{a_q}}}{\dfrac{\partial B^{t+1}\left(\boldsymbol{x}_a^G; \boldsymbol{x}_p^A, b^A\right)}{\partial x_{a_q}}}\right)}_{\text{TC change}} \underbrace{\left(\frac{\dfrac{\partial B^{t+1}\left(\boldsymbol{x}_a^G; \boldsymbol{x}_p^A, b^A\right)}{\partial x_{a_q}}}{\dfrac{\partial B^{t+1}\left(\boldsymbol{x}_a^M; \boldsymbol{x}^M, b^M\right)}{\partial x_{a_q}}} \frac{w_{x_{a_q}}^{t+1}}{w_{x_{a_q}}^t}\right)}_{\text{Non-TC change}}. \tag{3}$$

[6] Multiple pollutants can be generated when using multiple production inputs to produce outputs, i.e. coal power plants emit SO_2, NO_x and several toxics when producing electricity. However, each pollutant has different abatement processes. Thus, we consider a single pollutant generated by multiple production inputs and abated by potentially multiple abatement inputs.

[7] A given level of production inputs generates a pollutant which can be abated using abatement inputs; thus output does not appear in the equation.

[8] The notation $B^t(\boldsymbol{x}_a^A; \boldsymbol{x}_p^A, b^A)$ has the same meaning as $B^t(\boldsymbol{x}_a^A; \boldsymbol{x}_p^A)$ while we put b^A in the bracket to emphasize that $B^t(\boldsymbol{x}_a^A; \boldsymbol{x}_p^A) = b^A$.

[9] A non-technical change effect can also be decomposed on the period t technology. Decomposing the non-technical change effect on both the period t and the period $t + 1$ technologies allows a MAC ratio decomposition as described in the Appendix. However, components of the non-technical effect on the period t technology occasionally have infeasible solutions in practice as noted by Grifell-Tatje and Lovell (1999). This problem of infeasibility is similarly described in Ray and Mukherjee (1996).

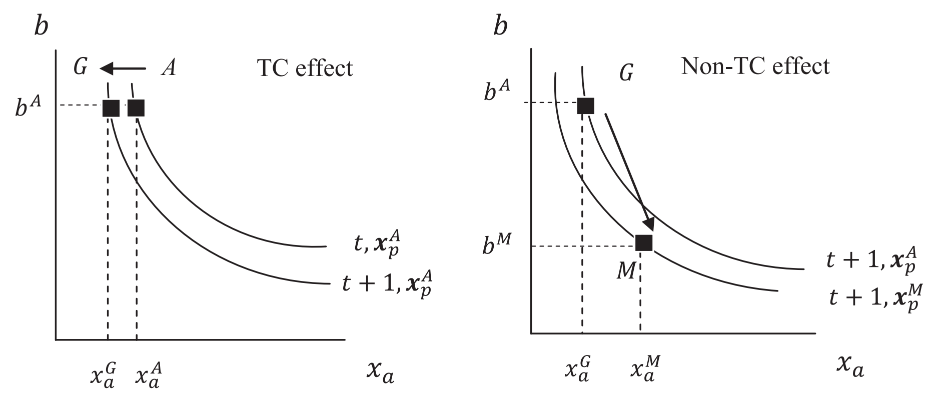

Fig. 2. Technical change effect and a non-technical change effect at $t + 1$ period.
Note we have chosen to measure technical change in terms of adjusting abatement inputs. Measuring in terms of bad outputs could lead to slightly different results.

Fig. 2 illustrates the decomposition in Eq. (3). The left graph shows the technical change effect when the firm reduces the amount of an abatement input from x_a^A to x_a^G while maintaining the same level of production inputs, $\boldsymbol{x}_p^A$, and emitting the same level of a pollutant, b^A. Note that if technical progress does not exist, the firm will be unable to reduce the abatement input. The right graph shows a non-technical change effect within the period $t + 1$, when the firm changes the amount of an abatement input from x_a^G to x_a^M reduce the amount of pollutant from b^A to b^M.[10]

The non-technical change effect is composed of three sub effects: 1) a pollutant level effect which is a measure of the change in abatement inputs due to the change of pollution level, 2) a production input scale effect which is a measure of the change in abatement inputs due to the change of outputs level, and 3) an abatement input cost effect which is a measure of the change in abatement inputs due to the change in the unit cost of abatement inputs. Fig. 3a illustrates the decomposition of the non-technical change effect on the period $t + 1$ pollutant frontier. Specifically, the figure shows the decomposition of the first term of the non-technical change effect in Table 1 where a firm changes the amount of abatement input from x_a^G to x_a^M in period $t + 1$. To capture the pollutant level effect when the production input scale effect at $t + 1$, assume that the firm uses information on abatement input costs from period $t + 1$, $\boldsymbol{w}_{x_a}^{t+1}$, to decide the abatement input mix satisfying the pollutant and production input level constraints. The first graph shows the abatement input cost effect and the abatement input cost changes from $\boldsymbol{w}_{x_a}^t = \left(w_{x_{a_1}}^t, w_{x_{a_2}}^t\right)$ to $\boldsymbol{w}_{x_a}^{t+1} = \left(w_{x_{a_1}}^{t+1}, w_{x_{a_2}}^{t+1}\right)$ where $\frac{w_{x_{a_1}}^t}{w_{x_{a_2}}^t} \le \frac{w_{x_{a_1}}^{t+1}}{w_{x_{a_2}}^{t+1}}$. To minimize the cost of abatement when the abatement input cost changes,[11] the firm adjusts the mix of abatement inputs from $\boldsymbol{x}_a^G$ to $\boldsymbol{x}_a^H$ in which abatement input 2 is used more than abatement input 1 due to the relative costs.[12] The second graph shows the pollutant level effect when the firm increases the use of abatement input from x_a^H to x_a^K to reduce the pollutant level from b^A to b^M while maintaining production input levels, $\boldsymbol{x}_p^A$. The third graph shows the production input scale effect when the firm reduces the use of abatement input from x_a^K to x_a^M and the production input level from $\boldsymbol{x}_p^A$ to $\boldsymbol{x}_p^M$ while still maintaining the pollutant level, b^M.

[10] Note that the right graph in Fig. 2 shows an arbitrary frontier shift under non-technical change. Depending on the data it would also be possible that the frontier shifted away from the origin and/or that the abatement input level associated with point M, x_a^M, could have been smaller than the abatement input level associated with point G, x_a^G.

[11] While maintaining the level of pollutant at b^A and the level of production inputs at $\boldsymbol{x}_p^A$ inconsistent with point A in period $t + 1$.

[12] Even if there is only an single abatement input, the abatement input cost effect will still characterize the effect on MAC due to the change in price of the single abatement input.

However, the sequence of non-technical change effect decomposition leads to different estimates of the pollutant level effect and the production input scale effect. Fig. 3b shows an alternative decomposition of the non-technical change effect on the period $t + 1$ pollutant frontier when interchanging the production input scale effect term and the pollutant effect term. Table 1 summarizes the two alternative non-technical change effect decompositions on the period $t + 1$ pollutant frontier.

The abatement input cost effect is consistent for both decompositions:

$$\frac{\dfrac{\partial B^{t+1}\left(\boldsymbol{x}_a^G; \boldsymbol{x}_p^A, b^A\right)}{\partial x_{a_q}}}{\dfrac{\partial B^{t+1}\left(\boldsymbol{x}_a^H; \boldsymbol{x}_p^A, b^A\right)}{\partial x_{a_q}}} \frac{w_{x_{a_q}}^{t+1}}{w_{x_{a_q}}^t}. \tag{4}$$

There are two different terms for the pollutant level effect; thus, we follow Färe et al. (1994) and take a geometric mean between these two terms to calculate the pollutant level effect. The pollutant level effect is written as:

$$\left(\frac{\dfrac{\partial B^{t+1}\left(\boldsymbol{x}_a^H;\boldsymbol{x}_p^A,b^A\right)}{\partial x_{a_q}}}{\dfrac{\partial B^{t+1}\left(\boldsymbol{x}_a^K;\boldsymbol{x}_p^A,b^M\right)}{\partial x_{a_q}}} \times \frac{\dfrac{\partial B^{t+1}\left(\boldsymbol{x}_a^L;\boldsymbol{x}_p^M,b^A\right)}{\partial x_{a_q}}}{\dfrac{\partial B^{t+1}\left(\boldsymbol{x}_a^M;\boldsymbol{x}_p^M,b^M\right)}{\partial x_{a_q}}} \right)^{\frac{1}{2}}. \tag{5}$$

Finally, the production input scale effect is written as:

$$\left(\frac{\dfrac{\partial B^{t+1}\left(\boldsymbol{x}_a^H;\boldsymbol{x}_p^A,b^A\right)}{\partial x_{a_q}}}{\dfrac{\partial B^{t+1}\left(\boldsymbol{x}_a^L;\boldsymbol{x}_p^M,b^A\right)}{\partial x_{a_q}}} \times \frac{\dfrac{\partial B^{t+1}\left(\boldsymbol{x}_a^K;\boldsymbol{x}_p^A,b^M\right)}{\partial x_{a_q}}}{\dfrac{\partial B^{t+1}\left(\boldsymbol{x}_a^M;\boldsymbol{x}_p^M,b^M\right)}{\partial x_{a_q}}} \right)^{\frac{1}{2}}. \tag{6}$$

To compute the technical change effect and the non-technical change effect using the MAC ratio (3), the marginal products of the abatement inputs (rigorously defined in Section 3.4) need to be estimated at both the observed points (A and M) and unobserved points on the $t + 1$ pollutant frontier (G, H, K, and L), all points are shown in Fig. 3a and b.

3. The estimation method

This section describes the estimation method to measure the technical change effect on MAC. In Section 3.1, we introduce contemporaneous pollutant frontiers in which random noise is considered and each period pollutant frontier is estimated by using the Stochastic Nonparametric Envelopment of Z-Data (StoNEZD) method (Johnson and Kuosmanen, 2011, 2012; Kuosmanen and Kortelainen, 2012). The

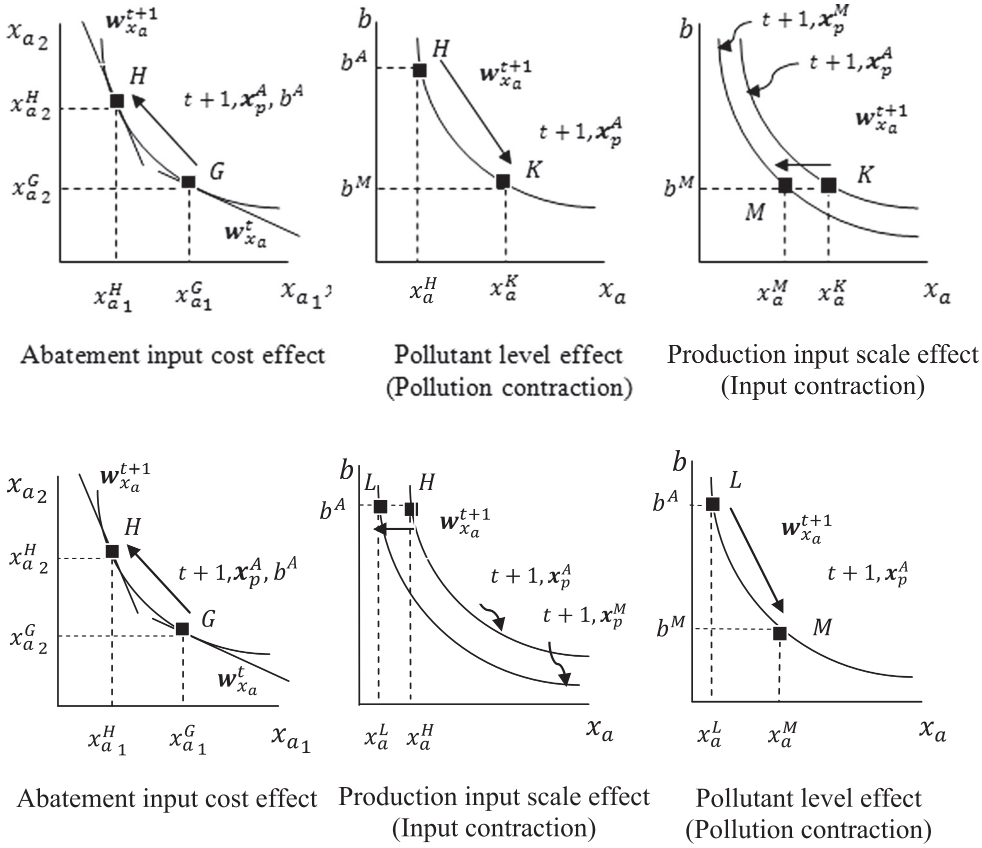

Fig. 3. a. The first decomposition of a non-technical change effect at period $t+1$. b. The second decomposition of a non-technical change effect at period $t+1$.

StoNEZD method estimates a pollutant frontier by solving the CNLS problem (Hildreth, 1954; Kuosmanen, 2008) while simultaneously controlling for the effect of contextual variables such as vintages of equipment. Based on a contemporaneous pollutant frontier, we develop a method to estimate the sequential pollutant frontiers described in Section 3.2. The sequential method consists of estimating fitted pollutant values by solving the modified CNLS problem. Then these fitted pollutant values are used to construct a series of unique piecewise linear pollutant frontiers by applying the technique to construct unique CNLS production frontiers in Kuosmanen (2008) with the sequential DEA technique in Tulkens and Van den Eeckaut (1995). Based on the estimated sequential pollutant frontiers, we find the unobserved abatement cost minimization points G, H, L and K by solving the set of linear programs described in Section 3.3. Section 3.4 describes how to find marginal products of abatement inputs at specific points on a piecewise linear pollutant frontier.

3.1. The estimation of a contemporaneous pollutant frontier

Consider a pollutant function characterized by the pollutant equation with a multiplicative disturbance term

$$b_i^t = B^t\left(\boldsymbol{x}_{ai}^{\ t}, \boldsymbol{x}_{pi}^{\ t}\right)\exp\left(\epsilon_i^t\right) \qquad \forall i = 1, \ldots, n; \forall t = 1, \ldots, T \tag{7}$$

where b_i^t, $\boldsymbol{x}_{ai}^t$, and $\boldsymbol{x}_{pi}^t$ denote the pollutant, abatement inputs, and production inputs of firm i at period t, B^t is a pollutant function at period t and ϵ_i^t is a composite disturbance term of firm i at period t. The multiplicative disturbance term in an arbitrary period t can be written as:

$$\epsilon_i^t = v_i^t + u_i^t + \boldsymbol{\delta}^{t\prime}\boldsymbol{z}_i^t \qquad \forall i = 1, \ldots, n;\ \forall t = 1, \ldots, T \tag{8}$$

where v_i^t is a random noise of firm i at period t, $\boldsymbol{\delta}^{t\prime}\boldsymbol{z}_i^t$ is the technical inefficiency of firm i at period t that is explained by the contextual variables, and u_i^t is the technical inefficiency of firm i at period t that is not explained by the contextual variable. Note, $\boldsymbol{z}_i^t \in R^r$ are contextual variables at period t and $\boldsymbol{\delta}^t \in R^r$ are coefficients that capture the average effect of contextual variables on deviation from the frontier pollutant function at period t. Assume random noise is i.i.d and normally distributed, $v_i^t \sim N(0, \sigma_v^2)$ and technical inefficiency is i.i.d and half normal distributed $u_i^t \sim |N(0, \sigma_u^2)|$. We denote that the expected inefficiency $\mu^t = E(u_i^t) > 0\ \forall\ t = 1, \ldots, T$.

Applying the log transformation to Eq. (7), the regression model is written as

$$\begin{aligned} \ln b_i^t &= \ln B^t\left(\boldsymbol{x}_{ai}^{\ t}, \boldsymbol{x}_{pi}^{\ t}\right) + \epsilon_i^t \\ &= \ln B^t\left(\boldsymbol{x}_{ai}^{\ t}, \boldsymbol{x}_{pi}^{\ t}\right) + \boldsymbol{\delta}^{t\prime}\boldsymbol{z}_i^t + v_i^t + u_i^t \\ &= \ln B^t\left(\boldsymbol{x}_{ai}^{\ t}, \boldsymbol{x}_{pi}^{\ t}\right) + \boldsymbol{\delta}^{t\prime}\boldsymbol{z}_i^t + \varphi_i^t \qquad \forall i = 1, \ldots, n;\ \forall t = 1, \ldots, T. \end{aligned} \tag{9}$$

The composite disturbance term in (9), φ_i^t, violates one of the Gauss–Markov properties that $E(\varphi_i^t) = E(v_i^t + u_i^t) = \mu^t > 0$; thus, the composite disturbance term is modified as

$$\begin{aligned} \ln b_i^t &= \left[\ln B^t\left(\boldsymbol{x}_{ai}^{\ t}, \boldsymbol{x}_{pi}^{\ t}\right) + \mu^t\right] + \boldsymbol{\delta}^{t\prime}\boldsymbol{z}_i^t + \left[\varphi_i^t - \mu^t\right] \\ &= \ln K^t\left(\boldsymbol{x}_{ai}^{\ t}, \boldsymbol{x}_{pi}^{\ t}\right) + \boldsymbol{\delta}^{t\prime}\boldsymbol{z}_i^t + \zeta_i^t \qquad \forall i = 1, \ldots, n; \forall t = 1, \ldots, T \end{aligned} \tag{10}$$

Table 1
The decomposition of a non-technical change effect at period $t + 1$.

Figure	Abatement input cost effect	Pollutant level effect	Production input scale effect
3a	$\dfrac{\frac{\partial B^{t+1}\left(\boldsymbol{x}_a^G;\boldsymbol{x}_p^A,b^A\right)}{\partial x_{aq}} \Big/ w_{x_{aq}}^{t+1}}{\frac{\partial B^{t+1}\left(\boldsymbol{x}_a^H;\boldsymbol{x}_p^A,b^A\right)}{\partial x_{aq}} \Big/ w_{x_{aq}}^{t}}$	$\dfrac{\frac{\partial B^{t+1}\left(\boldsymbol{x}_a^H;\boldsymbol{x}_p^A,b^A\right)}{\partial x_{aq}}}{\frac{\partial B^{t+1}\left(\boldsymbol{x}_a^K;\boldsymbol{x}_p^A,b^M\right)}{\partial x_{aq}}}$	$\dfrac{\frac{\partial B^{t+1}\left(\boldsymbol{x}_a^K;\boldsymbol{x}_p^A,b^M\right)}{\partial x_{aq}}}{\frac{\partial B^{t+1}\left(\boldsymbol{x}_a^M;\boldsymbol{x}_p^M,b^M\right)}{\partial x_{aq}}}$
3b	$\dfrac{\frac{\partial B^{t+1}\left(\boldsymbol{x}_a^G;\boldsymbol{x}_p^A,b^A\right)}{\partial x_{aq}} \Big/ w_{x_{aq}}^{t+1}}{\frac{\partial B^{t+1}\left(\boldsymbol{x}_a^H;\boldsymbol{x}_p^A,b^A\right)}{\partial x_{aq}} \Big/ w_{x_{aq}}^{t}}$	$\dfrac{\frac{\partial B^{t+1}\left(\boldsymbol{x}_a^L;\boldsymbol{x}_p^M,b^A\right)}{\partial x_{aq}}}{\frac{\partial B^{t+1}\left(\boldsymbol{x}_a^M;\boldsymbol{x}_p^M,b^M\right)}{\partial x_{aq}}}$	$\dfrac{\frac{\partial B^{t+1}\left(\boldsymbol{x}_a^H;\boldsymbol{x}_p^A,b^A\right)}{\partial x_{aq}}}{\frac{\partial B^{t+1}\left(\boldsymbol{x}_a^L;\boldsymbol{x}_p^M,b^A\right)}{\partial x_{aq}}}$

where $\zeta_i^t = \varphi_i^t - \mu^t$ is the modified composite disturbance term with $E(\zeta_i^t) = E(\varphi_i^t - \mu^t) = 0$ and $K^t(\boldsymbol{x}_{ai}^t, \boldsymbol{x}_{pi}^t) = B^t(\boldsymbol{x}_{ai}^t, \boldsymbol{x}_{pi}^t)\exp(\mu^t)$ is an average pollutant function.

For a specific period s, the contemporaneous CNLS problem to estimate the pollutant function with a modified composite disturbance is formulated as a non-linear programming problem with a quadratic object function:

$$\min_{\alpha^s,\boldsymbol{\gamma}^s,\boldsymbol{\rho}^s,\boldsymbol{\delta}^s,\zeta^s} \sum_{i=1}^{n} \zeta_i^{s2} \tag{11.1}$$

$$\text{s.t.} \quad \zeta_i^s = \ln(b_i^s) - \ln\left(\alpha_i^s + \boldsymbol{\gamma}_i^{s\prime}\boldsymbol{x}_{pi}^{\ s} + \boldsymbol{\rho}_i^{s\prime}\boldsymbol{x}_{ai}^{\ s}\right) - \boldsymbol{\delta}^{s\prime}\boldsymbol{z}_i^s \quad \forall i = 1,\dots,n \tag{11.2}$$

$$\alpha_i^s + \boldsymbol{\gamma}_i^{s\prime}\boldsymbol{x}_{pi}^{\ s} + \boldsymbol{\rho}_i^{s\prime}\boldsymbol{x}_{ai}^{\ s} \ge \alpha_h^s + \boldsymbol{\gamma}_h^{s\,\prime}\boldsymbol{x}_{pi}^{\ s} + \boldsymbol{\rho}_h^{s\,\prime}\boldsymbol{x}_{ai}^{\ s} \qquad \forall i, h = 1,\dots,n \tag{11.3}$$

$$\boldsymbol{\gamma}_i^s \ge 0 \text{ and } \boldsymbol{\rho}_i^s \le 0 \qquad \forall i = 1,\dots,n \tag{11.4}$$

where α_i^s, $\boldsymbol{\gamma}_i^s$ and $\boldsymbol{\rho}_i^s$ are the unknown parameters characterizing hyperplanes of the average pollutant frontier K^s. The objective function (Eq. (11.1)) minimizes the sum of squared disturbances. The equality constraints (Eq. (11.2)) define the modified composite disturbance terms. The inequality constraints (Eq. (11.3)) are a system of Afriat inequalities, Afrait (1972), imposing the underlying pollutant frontiers to be continuous and convex. The constraints (Eq. (11.4)) enforce that the frontier is monotonically increasing in $\boldsymbol{x}_{pi}^s$ and monotonically decreasing in $\boldsymbol{x}_{ai}^s$. Note that $\boldsymbol{\delta}^s$ is unrestricted in sign and that a positive sign on $\boldsymbol{\delta}$ implies that the contextual variable increases the observed level of pollutant.

Given the modified composite residuals, $\hat{\zeta}_i^S$ $\forall i$ from Eqs. (11.1)–(11.4), the method of moments is applied to separate the random noise and the technical inefficiency. The estimated standard deviation of the technical inefficiency and the random noise is written as

$$\hat{\sigma}_{u^s} = \sqrt[3]{\frac{\hat{M}_3}{\left(\frac{2}{\pi}\right)\left(\frac{4}{\pi} - 1\right)}} \tag{12}$$

$$\hat{\sigma}_{v^s} = \sqrt{\hat{M}_2 - \left(\frac{\pi - 2}{\pi}\right)\hat{\sigma}_{u^s}^2} \tag{13}$$

where $\hat{M}_2 = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{\zeta}_i^S - \hat{E}(\zeta_i^s)\right)^2$ and $\hat{M}_3 = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{\zeta}_i^S - \hat{E}(\zeta_i^s)\right)^3$ are the second and the third sample central moment of the modified composite residuals and $\hat{E}(\zeta_i^s) = \frac{1}{n}\sum_{i=1}^{n}\hat{\zeta}_i^S$ is the sample mean of modified composite residuals. $\hat{M}_3$ in Eq. (12) should be positive so that the estimated $\hat{\sigma}_{u^s}$ is positive. Intuitively, the composite residuals should distribute with a positive skew reflecting the presence of the technical inefficiency. The expected technical inefficiency is then calculated by

$$\hat{\mu}^S = \hat{\sigma}_{u^s}\sqrt{2/\pi}. \tag{14}$$

There are two alternatives: 1) if technical inefficiency exists and is not captured by the contextual variables, then $\mu^s > 0$ or 2) the contextual variables may capture most of the deviations from a normal residual term so that $\mu^s \approx 0$. To identify which alternative is more appropriate, the skewness of residuals is empirically investigated using the methods described in Kuosmanen and Fosgerau (2009).

The parameter estimates from Eqs. (11.1)–(11.4), $\hat{\alpha}_i^{\ s}$, $\hat{\boldsymbol{\gamma}}_i^{\ s}$ and $\hat{\boldsymbol{\rho}}_i^{\ s}$, need not be unique; however, the fitted values $\hat{b}_i^{\ S}$, $\forall i$ are unique. To address the non-uniqueness issue, the unique parameters characterizing hyperplanes of the pollutant frontier in an arbitrary period s at $(\boldsymbol{x}_a^{\ s}, \boldsymbol{x}_{pi}^{\ s})$ can be estimated by solving the following linear programming problem[13]:

$$\begin{aligned} &\max_{\alpha^s,\boldsymbol{\gamma}^s,\boldsymbol{\rho}^s} \alpha^s + \boldsymbol{\gamma}^{s\prime}\boldsymbol{x}_{pi}^{\ s} + \boldsymbol{\rho}^{s\prime}\boldsymbol{x}_a^{\ s} \\ \text{s.t.} \quad &\alpha^s + \boldsymbol{\gamma}^{s\prime}\boldsymbol{x}_{pi}^{\ s} + \boldsymbol{\rho}^{s\prime}\boldsymbol{x}_{ai}^{\ s} \le \hat{b}_i^{\ s} \qquad \forall i = 1,\dots,n \\ &\boldsymbol{\gamma}^s \ge 0 \text{ and } \boldsymbol{\rho}^s \le 0 \end{aligned} \tag{15}$$

where $\hat{b}_i^{\ s} = \left(\hat{\alpha}_i^{\ s} + \hat{\boldsymbol{\gamma}}_i^{\ s\prime}\boldsymbol{x}_{pi}^{\ s} + \hat{\boldsymbol{\rho}}_i^{\ s\prime}\boldsymbol{x}_{ai}^{\ s}\right)\exp(-\hat{\mu}^s)$ $\forall i$ are the fitted pollutant values in an arbitrary period s. Solving the problem (Eq. (15)) for all periods allows us to obtain the unique hyperplanes of the pollutant frontier for all periods.

Note that the estimated contemporaneous pollutant frontiers described in this section might satisfy a sequential pollutant frontier condition if a technical progress is significant enough so that the estimated frontiers in each period do not cross. However, for an arbitrary data set, this method is not guaranteed to generate sequential pollutant frontiers. Therefore, we propose the solution method described in the next section.

3.2. The estimation of sequential pollutant frontiers in multiple periods

Let $t+$ be the set of periods greater than t, $t+ = \{s|s > t\}$. Using the concept of sequential production functions, meaning that technical regress is not possible (see Fig. 2), the condition between the pollutant frontier at period t and $t+$ can be written as:

$$B^{t+}\left(\boldsymbol{x}_a, \boldsymbol{x}_p\right) \le B^t\left(\boldsymbol{x}_a, \boldsymbol{x}_p\right) \qquad \forall t = 1,\dots,T-1. \tag{16}$$

Condition (16) indicates that the production possibility set in $t + 1$ includes the production possibility set from period t. Consider a frontier pollutant function using a CNLS representor function[14], then $B^t(\boldsymbol{x}_a, \boldsymbol{x}_p) = \max_h\{\alpha_h^t + \boldsymbol{\gamma}_h^t{}'\boldsymbol{x}_p + \boldsymbol{\rho}_h^t{}'\boldsymbol{x}_a\}$ and $B^{t+}(\boldsymbol{x}_a, \boldsymbol{x}_p) = \max_h\{\alpha_h^{t+} + \boldsymbol{\gamma}_h^{t+}{}'\boldsymbol{x}_p + \boldsymbol{\rho}_h^{t+}{}'\boldsymbol{x}_a\}$; thus, condition (16) can be written as:

$$\max_h\left\{\alpha_h^{t+} + \boldsymbol{\gamma}_h^{t+\prime}\boldsymbol{x}_{p_i} + \boldsymbol{\rho}_h^{t+\prime}\boldsymbol{x}_{a_i}\right\} \le \max_h\left\{\alpha_h^t + \boldsymbol{\gamma}_h^{t\prime}\boldsymbol{x}_{p_i} + \boldsymbol{\rho}_h^{t\prime}\boldsymbol{x}_{a_i}\right\} \quad \forall i, h = 1,\dots n;\ \forall t = 1,\dots,T-1. \tag{17}$$

[13] The uniqueness issue has been discussed in Kuosmanen (2008). This problem is similar to Eq. (4.4) in Kuosmanen (2008) which estimates the unique lower envelope $\hat{g}_{min}$.
[14] The representor function for a production function is stated in Eq. (4.1) in Kuosmanen (2008).

For a production unit observed at two points in time, $(\boldsymbol{x}_{pi}^t, \boldsymbol{x}_{ai}^t)$ and $(\boldsymbol{x}_{pi}^{t+}, \boldsymbol{x}_{ai}^{t+})$, a CNLS problem Eqs. (11.1)–(11.4) will assign a pollutant frontier parameter for each observation such that $B^t(\boldsymbol{x}_{ai}^t, \boldsymbol{x}_{pi}^t) = \max_h \{\alpha_h^t + \boldsymbol{\gamma}_h^t{}'\boldsymbol{x}_{pi}^t + \boldsymbol{\rho}_h^t{}'\boldsymbol{x}_{ai}^t\} = \alpha_i^t + \boldsymbol{\gamma}_i^t{}'\boldsymbol{x}_{pi}^t + \boldsymbol{\rho}_i^t{}'\boldsymbol{x}_{ai}^t$ and $B^{t+}(\boldsymbol{x}_{ai}^{t+}, \boldsymbol{x}_{pi}^{t+}) = \max_h \{\alpha_h^{t+} + \boldsymbol{\gamma}_h^{t+}{}'\boldsymbol{x}_{pi}^{t+} + \boldsymbol{\rho}_h^{t+}{}'\boldsymbol{x}_{ai}^{t+}\} = \alpha_i^{t+} + \boldsymbol{\gamma}_i^{t+}{}'\boldsymbol{x}_{pi}^{t+} + \boldsymbol{\rho}_i^{t+}{}'\boldsymbol{x}_{ai}^{t+}$.

Thus, condition (17) can be written as:

$$\begin{aligned}
&\max_h \left\{\alpha_h^{t+} + \boldsymbol{\gamma}_h^{t+\prime}\boldsymbol{x}_{pi}^{\ t} + \boldsymbol{\rho}_h^{t+\prime}\boldsymbol{x}_{ai}^{\ t}\right\} \le \alpha_i^t + \boldsymbol{\gamma}_i^{t\prime}\boldsymbol{x}_{pi}^{\ t} + \boldsymbol{\rho}_i^{t\prime}\boldsymbol{x}_{ai}^{\ t} \\
\text{and}\quad &\alpha_i^{t+} + \boldsymbol{\gamma}_i^{t+\prime}\boldsymbol{x}_{pi}^{\ t+} + \boldsymbol{\rho}_i^{t+\prime}\boldsymbol{x}_{ai}^{\ t+} \le \max_h \left\{\alpha_h^t + \boldsymbol{\gamma}_h^{t\prime}\boldsymbol{x}_{pi}^{\ t+} + \boldsymbol{\rho}_h^{t\prime}\boldsymbol{x}_{ai}^{\ t+}\right\} \\
&\forall i, h = 1, \ldots n;\ \forall t = 1, \ldots, T-1.
\end{aligned} \tag{18}$$

Note that the sequential frontier condition (Eq. (18)) imposes the sequential relationship among pollutant functions; however, if unexplained technical inefficiency is significant, $\mu^s > 0$, then the CNLS problem should be solved adjusting the hyperplanes of the pollutant function for technical inefficiency. To formulate the CNLS problem satisfying the pollutant function properties and the sequential condition, the disturbance term is written as

$$\xi_i^t = v_i^t \qquad \forall i = 1, \ldots, n;\ \forall t = 1, \ldots, T \tag{19}$$

where v_i^t is a random noise at period t and the modified log pollutant level is written as

$$\ln\left(b_i^t\right) - \hat{\mu}^t \qquad \forall i = 1, \ldots, n; \forall t = 1, \ldots, T \tag{20}$$

where $\hat{\mu}^t$ is the expected technical inefficiency at period t. Combining the contemporaneous CNLS problem (Eqs. (11.1)–(11.4)) and the sequential condition (Eq. (18)) with the disturbance term (Eq. (19)) and modified log pollutant level (Eq. (20)), the sequential CNLS problem is formulated as

$$\min_{\alpha^t, \boldsymbol{\gamma}^t, \boldsymbol{\rho}^t, \boldsymbol{\delta}^t, \xi^t} \sum_{t=1}^{T}\sum_{i=1}^{n} \xi_i^{t^2} \tag{21.1}$$

$$\text{s.t}\ \xi_i^t = \left(\ln b_i^t - \hat{\mu}^t\right) - \ln\left(\alpha_i^t + \boldsymbol{\gamma}_i^{t\prime}\boldsymbol{x}_{pi}^{\ t} + \boldsymbol{\rho}_i^{t\prime}\boldsymbol{x}_{ai}^{\ t}\right) - \boldsymbol{\delta}^{t\prime}\boldsymbol{z}_i^t \qquad \forall i = 1, \ldots, n;\ \forall t = 1, \ldots, T \tag{21.2}$$

$$\alpha_i^t + \boldsymbol{\gamma}_i^{t\prime}\boldsymbol{x}_{pi}^{\ t} + \boldsymbol{\rho}_i^{t\prime}\boldsymbol{x}_{ai}^{\ t} \ge \alpha_h^t + \boldsymbol{\gamma}_h^{t\prime}\boldsymbol{x}_{pi}^{\ t} + \boldsymbol{\rho}_h^{t\prime}\boldsymbol{x}_{ai}^{\ t} \qquad \forall i, h = 1, \ldots, n;\ \forall t = 1, \ldots, T \tag{21.3}$$

$$\max_h \left\{\alpha_h^{t+} + \boldsymbol{\gamma}_h^{t+\prime}\boldsymbol{x}_{pi}^{\ t} + \boldsymbol{\rho}_h^{t+\prime}\boldsymbol{x}_{ai}^{\ t}\right\} \le \alpha_i^t + \boldsymbol{\gamma}_i^{t\prime}\boldsymbol{x}_{pi}^{\ t} + \boldsymbol{\rho}_i^{t\prime}\boldsymbol{x}_{ai}^{\ t} \qquad \forall i, h = 1, \ldots, n;\ \forall t = 1, \ldots, T-1 \tag{21.4}$$

$$\begin{aligned}
&\alpha_i^{t+} + \boldsymbol{\gamma}_i^{t+\prime}\boldsymbol{x}_{pi}^{\ t+} + \boldsymbol{\rho}_i^{t+\prime}\boldsymbol{x}_{ai}^{\ t+} \qquad \forall i, h = 1, \ldots, n \\
&\quad \le \max_h \left\{\alpha_h^t + \boldsymbol{\gamma}_h^{t\prime}\boldsymbol{x}_{pi}^{\ t+} + \boldsymbol{\rho}_h^{t\prime}\boldsymbol{x}_{ai}^{\ t+}\right\} \\
&\qquad \forall t = 1, \ldots, T-1
\end{aligned} \tag{21.5}$$

$$\boldsymbol{\gamma}_i^t \ge 0 \text{ and } \boldsymbol{\rho}_i^t \le 0 \qquad \forall i = 1, \ldots, n;\ \forall t = 1, \ldots, T \tag{21.6}$$

where α_i^t, $\boldsymbol{\gamma}_i^t$ and $\boldsymbol{\rho}_i^t$ are parameters characterizing hyperplanes of the sequential frontier pollutant function at period t, B^t. The objective function (Eq. (21.1)) minimizes the sum of squared of disturbances summed over multiple periods. The equality constraints (Eq. (21.2)) define the disturbance using the modified log pollutant level (Eq. (20)). Constraints (21.3) and (21.6) are the same as constraints (11.3) and (11.4) in the contemporaneous CNLS problem. Constraints (21.4) and (21.5) enforce the sequential frontier condition. An iterative procedure is needed to solve the sequential CNLS problem (Eqs. (21.1)–(21.5)). The proposed iterative procedure is the modified version of the algorithm proposed in Lee et al. (2013); see the Appendix for details.

The StoNEZD estimator for $\boldsymbol{\delta}$ from the problem (Eqs. (21.1)–(21.5)) is statistically unbiased, consistent and asymptotically normally distributed, as $\hat{\boldsymbol{\delta}} \sim_a N\left(\boldsymbol{\delta}, (\sigma_v^2)\left(\boldsymbol{Z}'\boldsymbol{Z}\right)^{-1}\right)$,[15] where $\boldsymbol{Z} = (\boldsymbol{z}_1, \ldots, \boldsymbol{z}_n)'$, thus a standard t-test will be used in empirical result Section 5 to test the statistical significance of $\boldsymbol{\delta}$ effect on the pollutant level.

Similar to the contemporaneous pollutant frontier case, the parameter estimates from the problem (Eqs. (21.1)–(21.5)), $\hat{\alpha}_i^{\ t}$, $\hat{\boldsymbol{\gamma}}_i^{\ t}$ and $\hat{\boldsymbol{\rho}}_i^{\ t}$ $\forall i$; $\forall t$, need not be unique, but the fitted value $\hat{b}_i^{\ t}$ $\forall i$ and $\forall\, t$ are. To find the unique hyperplanes for sequential pollutant frontiers, we combine the linear programming problem (Eq. (15)) with the sequential DEA method and impose the conditions that the frontier estimated in time period s uses the data from all previous periods $\left(\boldsymbol{x}_{pi}^t,\ \boldsymbol{x}_{ai}^t,\ \hat{b}_i^{\ t}\right)$ $\forall i = 1, \ldots, n$; $\forall t = 1,\ \ldots,\ s$. The unique parameters characterizing hyperplanes of sequential pollutant frontier in an arbitrary period s at $(\boldsymbol{x}_a^{\ s},\ \boldsymbol{x}_p^{\ s})$ can be estimated by solving the following linear programming problem:

$$\begin{aligned}
&\max_{\alpha^s, \boldsymbol{\gamma}^s, \boldsymbol{\rho}^s} \alpha^s + \boldsymbol{\gamma}^s\boldsymbol{x}_p^{\ s} + \boldsymbol{\rho}^s\boldsymbol{x}_a^{\ s} \\
&\text{s.t}\ \alpha^s + \boldsymbol{\gamma}^s\boldsymbol{x}_{pi}^{\ t} + \boldsymbol{\rho}^s\boldsymbol{x}_{ai}^{\ t} \le \hat{b}_i^{\ t} \qquad \forall i = 1, \ldots, n;\ \forall t = 1, \ldots, s \\
&\quad \boldsymbol{\gamma}^s \ge 0 \text{ and } \boldsymbol{\rho}^s \le 0
\end{aligned} \tag{22}$$

where $\hat{b}_i^{\ t} = \hat{\alpha}_i^{\ t} + \hat{\boldsymbol{\gamma}}_i^{\ t'}\boldsymbol{x}_{pi}^{\ t} + \hat{\boldsymbol{\rho}}_i^{\ t'}\boldsymbol{x}_{ai}^{\ t}$ $\forall t = 1, \ldots, s$ and $\hat{\alpha}_i^{\ t}$, $\hat{\boldsymbol{\gamma}}_i^{\ t}$ and $\hat{\boldsymbol{\rho}}_i^{\ t}$ $\forall i$; $\forall t$ are the parameter estimates from the problem (Eqs. (21.1)–(21.5)). Solving the problem (Eq. (22)) for all periods allows us to obtain the unique hyperplanes of the sequential pollutant frontier for all periods.

3.3. Finding abatement cost minimization points on estimated pollutant frontiers

In this section, we describe a method to identify the unobserved abatement cost minimization points, G, H, L and K, i.e. the solutions of the abatement cost minimization problem, $\min_{\boldsymbol{x}_a}\left\{\boldsymbol{w}_{x_a}{}'\boldsymbol{x}_a : B(\boldsymbol{x}_a; \boldsymbol{x}_p) \le b\right\}$. Considering time period s and given an estimated pollutant frontier, $\hat{B}^s$, the unobserved cost minimization points can be found by solving the cost minimization problem, $\min_{\boldsymbol{x}_a}\left\{\boldsymbol{w}_{x_a}{}'\boldsymbol{x}_a : \hat{B}^s(\boldsymbol{x}_a; \boldsymbol{x}_p) \le b\right\}$. Using the explicit representor function for the pollutant frontier $\hat{B}^s(\boldsymbol{x}_a, \boldsymbol{x}_p) = \max_i\left\{\hat{\alpha}_i^{\ s} + \hat{\boldsymbol{\gamma}}_i^{\ s\prime}\boldsymbol{x}_p + \hat{\boldsymbol{\rho}}_i^{\ s\prime}\boldsymbol{x}_a\right\}$ and the estimated parameters $(\hat{\alpha}_i^{\ s}, \hat{\boldsymbol{\gamma}}_i^{\ s}, \hat{\boldsymbol{\rho}}_i^{\ s})$ from Eq. (22), the solution to the cost minimization problem is found by solving the following linear programming problem:

$$\begin{aligned}
&\min_{\boldsymbol{x}_a} \boldsymbol{w}_{x_a}{}'\boldsymbol{x}_a \\
\text{s.t}\quad &\alpha_i^{\ s} + \hat{\boldsymbol{\gamma}}_i^{\ s\prime}\boldsymbol{x}_p + \hat{\boldsymbol{\rho}}_i^{\ s\prime}\boldsymbol{x}_a \le b \qquad \forall i = 1, \ldots n \\
&\boldsymbol{x}_a \ge 0.
\end{aligned} \tag{23}$$

Given abatement input cost $\boldsymbol{w}_{x_a}$, the level of the production input $\boldsymbol{x}_p$ and the level of the pollutant b, we can find unobserved points G, H, L and K for each observation by solving the linear programming problem based on Eq. (23).[16]

[15] When technical inefficiency exists, the StoNEZD estimator for $\boldsymbol{\delta}$ is still statistically unbiased, consistent and asymptotically normally distributed as $\hat{\boldsymbol{\delta}} \sim_a N\left(\boldsymbol{\delta}, (\sigma_v^2 + \sigma_u^2)\left(\boldsymbol{Z}'\boldsymbol{Z}\right)^{-1}\right)$, see Theorem 1 and 2 in Johnson and Kuosmanen (2011) for details.

[16] This involves solving four sets of linear programs for each observation (see the Appendix).

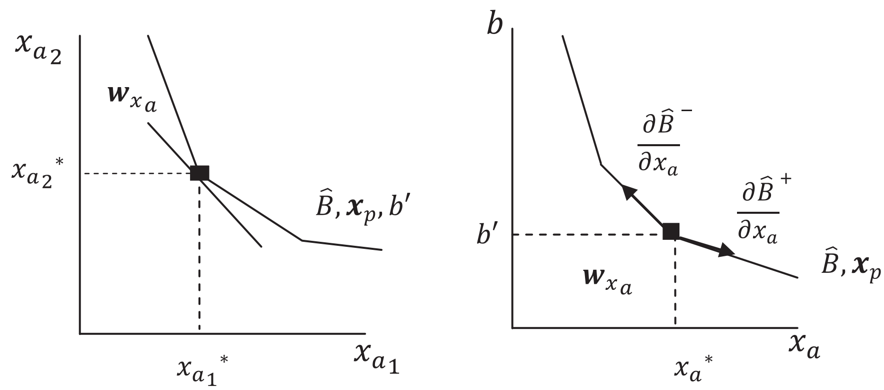

Fig. 4. The abatement cost minimization occurs at edge points where the marginal product of an abatement input is non-unique.

Table 2
Statistics for bituminous coal-fired boilers in the U.S. (n = 325).

Year	Variable	Mean	Std. dev	Min.	Max.
2000	Heat input	18,829	15,238	866	79,135
	NO_x	4.32	3.48	0.25	18.68
	Abatement input	10,033	10,398	0	52,360
	Abatement input price	0.07	0.08	0	0.50
2004	Heat input	17,881	15,068	248	82,628
	NO_x	3.15	2.63	0.05	14.69
	Abatement input	14,917	16,223	0	76,999
	Abatement input price	0.18	0.18	0	0.64
2008	Heat input	17,800	15,657	57	93,785
	NO_x	2.60	2.37	0.02	16.53
	Abatement input	16,714	17,759	0	87,371
	Abatement input price	0.23	0.20	0	0.65

Note: Unit of heat input, NO_x, abatement input and abatement input price are $10^3 \times$ mmBtu, $10^3 \times$ ton, $10^3 \times$ mmBtu, and $10^3 \times$ \$/mmBtu, respectively.

3.4. The estimation of the marginal product of an abatement input

The remaining task is to compute the marginal product of an abatement input at both observed and unobserved points. The marginal product of an abatement input is equivalent to a partial derivative of the pollutant frontier with respect to an abatement input, which we approximate as the slope on the estimated pollutant frontier. However, computational difficulty arises when the estimated frontier is not smooth everywhere, such as the piecewise linear frontiers estimate in this paper, because the function is non-differentiable at edge points (Charnes et al., 1985). Specifically, the discontinuity of slopes at edge points causes non-unique partial derivatives. Moreover, as shown in Fig. 4, the abatement cost minimization points on a piecewise linear pollutant frontier are likely to exist at edge points, meaning that a partial derivative will differ when taken from the left or from the right. To estimate marginal products of an abatement input, we use the method in Rosen et al. (1998) to find the partial derivatives of a piecewise linear function.

The left and right partial derivatives of the pollutant frontier with respect to x_{aq} at $(\boldsymbol{x}_a, \boldsymbol{x}_p)$ are respectively defined as:

$$\frac{\partial B\left(\boldsymbol{x}_a,\boldsymbol{x}_p\right)^-}{\partial x_{aq}} = \lim_{h\to 0^-} \frac{B\left(x_{a1},\dots,x_{aq}-h,\dots,x_{aQ},\boldsymbol{x}_p\right)-B\left(\boldsymbol{x}_a,\boldsymbol{x}_p\right)}{h} \quad (24a)$$

$$\frac{\partial B\left(\boldsymbol{x}_a,\boldsymbol{x}_p\right)^+}{\partial x_{aq}} = \lim_{h\to 0^+} \frac{B\left(x_{a1},\dots,x_{aq}+h,\dots,x_{aQ},\boldsymbol{x}_p\right)-B\left(\boldsymbol{x}_a,\boldsymbol{x}_p\right)}{h}. \quad (24b)$$

Let $(\boldsymbol{x}_a, \boldsymbol{x}_p)$ be the abatement cost minimizing production possibility on the pollutant frontier at period s obtained from solving (23). From (24a) and (24b), the left and right partial derivatives of the pollutant frontier at period s with respect to a particular abatement input q at $(\boldsymbol{x}_a, \boldsymbol{x}_p)$ can be estimated using the following:

$$\frac{\partial B^s\left(\boldsymbol{x}_a,\boldsymbol{x}_p\right)^-}{\partial x_{aq}} \approx -\frac{\hat{B}^s\left(\boldsymbol{x}_a{}^-,\boldsymbol{x}_p\right)-\hat{B}^s\left(\boldsymbol{x}_a,\boldsymbol{x}_p\right)}{\varepsilon} \quad (25a)$$

$$\frac{\partial B^s\left(\boldsymbol{x}_a,\boldsymbol{x}_p\right)^+}{\partial x_{aq}} \approx \frac{\hat{B}^s\left(\boldsymbol{x}_a{}^+,\boldsymbol{x}_p\right)-\hat{B}^s\left(\boldsymbol{x}_a,\boldsymbol{x}_p\right)}{\varepsilon} \quad (25b)$$

where $\varepsilon > 0$ is a small positive number, $\boldsymbol{x}_a{}^- = \left(x_{a1}, x_{a2}, .., x_{aq}-\varepsilon, \dots, x_{aQ}\right)$, $\boldsymbol{x}_a{}^+ = \left(x_{a1}, x_{a2}, .., x_{aq}+\varepsilon, \dots, x_{aQ}\right)$ and $\hat{B}^s\left(\boldsymbol{x}_a,\boldsymbol{x}_p\right) = \max_i\{\hat{\alpha}_i{}^s + \hat{\boldsymbol{\gamma}}_i{}^{s\prime}\boldsymbol{x}_p + \hat{\boldsymbol{\rho}}_i{}^{s\prime}\boldsymbol{x}_a\}$.[17]

While it is possible to use either $\frac{\partial B^s(\boldsymbol{x}_a,\boldsymbol{x}_p)^-}{\partial x_{aq}}$ or $\frac{\partial B^s(\boldsymbol{x}_a,\boldsymbol{x}_p)^+}{\partial x_{aq}}$ or an average as an estimate for a marginal product of an abatement input, we use $\frac{\partial B^s(\boldsymbol{x}_a,\boldsymbol{x}_p)^+}{\partial x_{aq}}$ because it consistent with the definition of MAC, i.e. an additional cost of abatement when using more abatement input to reduce one more unit of pollutant.

To summarize, the three-step estimation method to decompose the MAC ratio is:

1. Estimate the sequential pollutant frontiers:
   1.1 Estimate the expected technical inefficiency $\hat{\mu}^{l^t}\,\forall t = 1, \dots, T$ as described in Section 3.1.
   1.2 Estimate the fitted pollutant values, $\hat{b}_i^{\,t}\,\forall i = 1, \dots, n; \forall t = 1, \dots, T$ by using the algorithm for solving the sequential CNLS problem (Eqs. (21.1)–(21.5)) introduced in the Appendix.

[17] Note the subscript or superscript l on some parameters is to indicate the left-hand side derivative is used.

Table 3
Vintage variable as contextual variables.

Year boiler entered operation	Contextual variables	Number of boilers
1940–1959	z_1	136
1960–1979	z_2	154
1980–	NA	35

Table 4
Results of the skewness and kurtosis test of the CNLS residuals.

Year	Test statistics		P-values	
	$\sqrt{b_1}$	b_2	$\sqrt{b_1}$	b_2
2000	0.127	3.295	0.177	0.114
2004	−0.191	3.301	0.924	0.111
2008	−1.046	4.821	1.000	0.000

Table 5
MAC change decomposition for coal-fired boilers.[a,b]

Year	MAC change	Technical change effect	Non-technical change Effect	Number of boilers
2000–2004	1.300	0.717	1.810	172
2004–2008	1.148	0.735	1.561	229

[a] Subtracting unity from the values in the table and multiplying by 100 yields percentage changes.
[b] Note all the components of MAC change could only be calculated for a subset of boilers; the count is shown in the far right column, due to the projection of an observation not intersecting the frontier. This problem is particular serve for frontiers estimated accounting for noise. Section 2.2 describes the MAC change calculations using the $t+1$ data which we have used in the application. The problem was more severe for the period t data and using the geometric mean of the period t and period $t+1$ calculations would have further reduced the sample size. However, the calculations using the smaller data sets were similar in sign and magnitude.

1.3 For each period s, solve the linear programming problem (Eq. (22)) to obtain $(\hat{\alpha}_i^s, \hat{\boldsymbol{\gamma}}_i^s, \hat{\boldsymbol{\rho}}_i^s)$. Solving for all periods gives $\left(\hat{\alpha}_i^t, \hat{\boldsymbol{\gamma}}_i^t, \hat{\boldsymbol{\rho}}_i^t\right) \forall i = 1, \ldots, n; \forall\, t = 1, \ldots, T$.

2. For $\forall\, i = 1, \ldots, n$, find the unobserved abatement cost minimization points G, H, L and K by solving the linear programs based on Eq. (23).
3. Calculate a technical change effect and a non-technical change effect of MAC decomposition.
   3.1 For $\forall\, i = 1, \ldots, n$, find the marginal products to the right at points G, H, L and K using Eq. (25b).
   3.2 Estimate the technical change effect and non-technical change effect using Eq. (3), the abatement input cost effect using Eq. (4), the pollutant level effect using Eq. (5), and the production input scale effect using Eq. (6).

4. Data set

The panel boiler-level data consists of 325 boilers of U.S. bituminous coal power plants operating in 22 eastern states under the Clean Air Interstate Rule (CAIR) NO_x program. Most of these boilers were under the NO_x Budget Trading Program with the exception of 43 boilers operating in Florida, Georgia, Missouri, Mississippi and parts of Alabama. We analyze a technical change effect by investigating the data at three points in time: 2000, 2004, and 2008. In 2000, most of the boilers were not regulated by the NO_x Budget Trading Program, 2004 was the first year that most were affected by the NO_x Budget Trading Program,[18] and 2008 was the last year of the NO_x Budget Trading Program before the transition to the more stringent CAIR NO_x program. We restrict our data set by focusing on wall and tangential fired boilers, the two most widely used types of pulverized coal (PC) fired boilers. The selected boilers' sizes range between 65 and 1426 MW.

The production input, heat input (mmBtu), is used as a proxy for the amount and quality of coal in electricity production. The pollutant is NO_x. Data on heat input and NO_x are taken from the EPA acid rain program data base (EPA, 2011). The proxy of abatement input (mmBtu) is constructed to reflect abatement effort by using the information on boiler's maximum heat input rate, operating hours in a year, and performance of NO_x reduction conditioned on the type of abatement system. The NO_x abatement input cost ($/mmBtu) is estimated using capital cost information, fixed operation and maintenance (O & M) cost, and variable operation and maintenance cost as suggested in EPA (2010). Details regarding the measures of abatement input and the abatement input cost are constructed using the methods described in the Appendix. The summary statistics are reported in Table 2.

[18] The NO_x budget trading program was promulgated in 1998.

The contextual variables are the vintages of the boiler, defined as the time a boiler entered operation. Vintage is important because older boilers are likely to have different NO_x emission levels. Coal power plants with older vintage boilers typically produce less electricity with similar levels of fuel due to boiler depreciation. The vintages separated into three groups, 1940–1959, 1960–1979 and 1980–, are reported in Table 3.

5. Empirical results and analyses

The skewness of CNLS residuals is empirically tested using the methods in Kuosmanen and Fosgerau (2009). Table 4 reports the skewness $\left(\sqrt{b_1}\right)$ test statistics in which the null hypothesis H_0, disturbances are normally distributed, is tested against an alternative hypothesis H_1, disturbances are *positively* skewed. Table 4 also reports the additional information of the kurtosis (b_2) test statistics in which the null hypothesis H_0, disturbances are normal kurtosis, is tested against an alternative hypothesis H_1, disturbances are non-normal kurtosis[19]. For 2000 and 2004, the null hypothesis related to both $\sqrt{b_1}$ and b_2 tests cannot be rejected at the 10% significant level; thus, the result does not support the presence of technical inefficiency implying that $\sigma_u = 0$. For 2008, the null hypothesis cannot be rejected for the $\sqrt{b_1}$ test but is rejected for the b_2 test due to excess kurtosis. In this case, the presence of technical inefficiency is rejected implying that $\sigma_u = 0$, but assuming that the disturbance contains only random noise may be a poor specification[20]. In summation, we conclude there is not enough statistical evidence of the present of technical inefficiency in the sample implying that the expected technical inefficiency $\hat{\mu}^t = 0\ \forall t$.

The decomposition results for the change in MAC in 2000–2004 and 2004–2008 are reported in Table 5. The results are geometric averages over the number of boilers listed in the last column and the breakdowns of boilers excluded from the analysis are reported in the Appendix. Technical change accounts for 28.3% decline in MAC between 2000–2004 and 26.5% decline during 2004–2008 for our sample. However, MAC increases about 30% in 2000–2004 and 14.8% in 2004–2008, due to non-technical change.

Table 6 reports the decomposition of the non-technical change effect into a pollutant level effect, a production input scale effect, and an abatement input cost effect. On average, the abatement input cost effect increases MAC by 53.8% during 2000–2004 and 28% during 2004–2008, and is the largest contributor to the non-technical change effect. As

[19] The simulated distribution of the $\sqrt{b_1}$ and b_2 are constructed via a Monte Carlo simulation using $M = 10{,}000$ Pseudo-samples of $n = 325$ observations from $N(0, 1)$.
[20] This study chooses the model that failed the test with the smallest margin after testing alternative specifications that also failed the kurtosis test.

Table 6
The non-technical change effect decomposition for coal power plants.[a]

Year	Non-technical change effect	Pollutant level effect	Production input level effect	Abatement input cost effect
2000–2004	1.810	1.209	0.974	1.538
2004–2008	1.561	1.138	1.071	1.280

[a] Subtracting unity from the values in the table and multiplying by 100 yields percentage changes.

Table 7
Contextual variable parameter estimates.

Year	$\hat{\delta}_1$	*t*-Statistic	$\hat{\delta}_2$	*t*-Statistic
2000	0.274[a]	14.687	0.156[a]	8.887
2004	0.226[a]	11.532	0.163[a]	8.816
2008	0.218[a]	6.702	0.068[b]	2.235

[a] Significant at the 1% level or better.
[b] Significant at the 5% level or better.

plant operators began to install advanced abatement equipment, especially selective catalytic reduction (SCR) and selective non-catalytic reduction (SNCR), the higher capital and operational costs (EPA, 2010) of such systems resulted in higher MAC.

The pollutant level effect accounted for a 20.9% increase in MAC during 2000–2004 and 13.8% during 2004–2008. During these periods, power plants significantly lowered their NO_x emission levels for two reasons. Under the EPA's NO_x budget program, each state is required to reduce its NO_x emission cap every year, and affected power plants were allowed fewer NO_x allowances and therefore reduced their NO_x emission levels. Second, the NO_x budget program allowed operators to bank their unused allowances for future use; thus operators began to further reduce NO_x emissions. Other factors such as uncertain regulatory conditions also contributed to increased banking.

Finally, the results related to the production input scale effect are mixed; however, this effect has a limited contribution to changes in MAC when compared to the abatement input cost effect and the pollutant level effect. On average, the input scale effect contributed a 2.6% decrease in MAC during 2000–2004 and 7.1% increase in MAC during 2004–2008. In fact, on average, the amount of heat input decreased only by 4.96% in 2000–2004 and 0.44% in 2004–2008. On the other hand, NO_x levels decreased by 27.08% in 2000–2004 and 17.46% in 2004–2008. Coal power plants typically use coal-burning boilers to generate heat input, while gas-burning or oil-burning boilers are used for additional heat input generation during periods of increased demand for electricity. This is the primary reason why heat input levels are stable in our sample.

The effects of boiler vintages, δ_1 and δ_2, on the pollutant level are reported in Table 7. The results are similar to the results in Mekaroonreung and Johnson (2012) who found that both δ_1 and δ_2 are positively signed and significant. It implies that older vintages increase NO_x emissions. On average, boilers commissioned in 1940–1959 have 21.8%–27.4% higher NO_x emissions than those starting after 1980, while those commissioned during 1960–1979 have 6.8%–16.3% higher NO_x emissions than those entering operation after 1980. The vintage effect decreased in 2000–2008, possibly due to increased maintenance, upgrades, and replacement.

To summarize, several factors resulted in the MAC change during the NO_x budget program. A non-technical change effect was caused by operators adjusting their abatement inputs to lower NO_x levels while maintaining a given level of heat input and abatement input cost. Increases in NO_x marginal abatement cost primarily resulted from the higher capital and operational cost of the new abatement systems (the abatement input cost effect) and lower NO_x pollutant levels (the pollutant level effect) due to both programs. The boilers in our analysis consumed relatively constant amounts of heat input during 2000–2008; thus, changes in MAC were not attributed to changes in the heat input level effect. In 2000–2008, on average, technical change lowered the NO_x marginal abatement costs of coal power plants.

6. Conclusions and discussions

This paper described the effect of technical change on firms' MAC. We developed a new decomposition of the MAC change ratio consisting of a technical change effect and a non-technical change effect. The non-technical change effect was further decomposed into three subfactors, an abatement input cost effect, a pollutant level effect, and a production input scale effect. The decomposition allowed identification of the sources of MAC change. To measure each effect empirically, we developed a methodology consisting of three steps: 1) new nonparametric estimation method of sequential pollutant frontiers in stochastic framework, 2) calculating unobserved abatement cost minimization points based on estimated sequential pollutant frontiers, and 3) calculating MAC change decomposition based on marginal product of abatement inputs at unobserved abatement cost minimization points.

We applied the proposed methodology to a data set of 325 boilers in 134 U.S. bituminous coal power plants in 2000–2008. We found that the significant NO_x reduction and that the higher MAC was due to widespread use of advanced post-combustion abatement system such as SCR and SNCR. We conclude that even though technical change exists and lowers MAC, the technical change effect is overwhelmed by the effects of regulation and post-combustion equipment.

Our methodology focuses on abatement methods in which the abatement inputs can be assigned to specific pollutants. This is straightforward to implement for end-of-pipe abatement. However, identifying the methodology for assignment of change-in-process abatement inputs to specific pollutants is still an open research question. Alternatively the model could be adapted to treat change-in-process abatement inputs differently incorporating ideas from Färe et al. (2012). Further, additional data is available in EIA-767 survey such as regulation status, emission standards, and average coal nitrogen content that could be used to enrich future analysis of U.S. coal fired power plants.

An important question in the cap and trade program is whether emission permits should be given to polluting firms for free or they should be auctioned. Free and auctioned permits instrument provide different incentives for firms to promote innovation and diffusion, especially when technical change has different effects on MAC. Milliman and Prince (1989) state that if technical change decreases MAC, auction permits provide more incentive for industry to develop pollution control innovations across firms. On the other hand, Baker et al. (2008) conclude that if technical change increases MAC, free permits are a better instrument than auction permits. The results in this paper indicate that the NO_x control innovation and diffusion promotion in coal power plants could benefit from auctioning permits used in the CAIR NO_x program instead of giving away free permits as is currently done.

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Appendix A. Supplementary material

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References

Afriat, S., 1972. Efficiency estimation of production functions. Int. Econ. Rev. 8, 568–598.

Baker, E., Clarke, L., Weyant, J., 2006. Optimal technology R&D in the face to climate uncertainty. Climate Change 78, 157–179.

Baker, E., Clarke, L., Shittu, E., 2008. Technical change and the marginal cost of abatement. Energy Econ. 30, 2799–2816.

Balk, B.M., 2001. Scale efficiency and productivity change. J. Prod. Anal. 15, 159–183.

Bramoulle, Y., Olson, L.J., 2005. Allocation of pollution abatement under learning by doing. J. Public Econ. 89, 1935–1960.

Charnes, A., Cooper, W.W., Golany, B., Seiford, L., Stutz, J., 1985. Foundations of data envelopment analysis for Pareto–Koopmans efficient empirical production functions. J. Econ. 30, 91–107.

Diewert, W.E., 1980. Capital and the theory of productivity measurement. Am. Econ. Rev. 70, 260–267.

EPA (U.S. Environmental Protection Agency), 2009. The NO_x budget trading program: 2008 emission, compliance, and market analyses, Available at www.epa.gov/airmarkets/progress/NBP_1.html (Accessed 4 October 2011).

EPA (U.S. Environmental Protection Agency), 2010. Updates to EPA base case v3.02 EISA using the integrated planning model, Available at http://www.epa.gov/airtransport/pdfs/IPMUpdateDocumentation7-22-10.pdf (Accessed 8 July 2011).

EPA (U.S.Environmental Protection Agency), 2011. Clean air markets — data and maps: emissions, Available at http://camddataandmaps.epa.gov/gdm/index.cfm (Accessed 1 July 2011).

Färe, R., Grosskopf, S., Norris, M., Zhang, Z., 1994. Productivity growth, technical progress and efficiency change in industrialized countries. Am. Econ. Rev. 84, 66–83.

Färe, R., Grosskopf, S., Noh, D.W., Weber, W., 2005. Characteristics of a pollution technology: theory and practice. J. Econ. 126, 469–492.

Färe, R., Grosskopf, S., Pasurka, C., 2006. Social responsibility: U.S. power plants 1985–1998. J. Prod. Anal. 26 (3), 259–267.

Färe, R., Grosskopf, S., Pasurka, C., 2007. Pollution abatement activities and traditional measures of productivity: a joint production perspective. Ecol. Econ. 62 (3–4), 673–682.

Färe, Rolf, Grosskopf, S., Pasurka Jr., Carl, 2010. "Toxic releases: an environmental performance index for coal-fired power plants,"Elsevier Energy Econ. 32 (1), 158–165 (January).

Färe, R., Grosskopf, S., Pasurka, C., Weber, W., 2012. Substitutability among undesirable outputs. Appl. Econ. 44 (No. 1), 39–47.

Färe, R., Grosskopf, S., Pasurka, C., 2014. Potential gains from trading bad outputs: the case of U.S. electric power plants. Resour. Energy Econ. 36, 99–112.

Fisher, C., Parry, I.W.H., Pizer, W., 2003. Instrument choice for environmental protection when technological innovation is endogenous. J. Environ. Econ. Manag. 45, 523–545.

Grifell-Tatje, E., Lovell, C.A.K., 1999. Profits and productivity. Manag. Sci. 45, 1177–1193.

Hicks, J.R., 1966. The Theory of Wages, 2nd ed. Macmillan, London.

Hildreth, C., 1954. Point estimates of ordinates of concave functions. J. Am. Stat. Assoc. 49, 598–619.

Johnson, A.L., Kuosmanen, T., 2011. One-stage estimation of the effects of operational conditions and practices on productive performance: asymptotically normal and efficient, root-*n* consistent StoNEZD method. J. Prod. Anal. 36, 219–230.

Johnson, A.L., Kuosmanen, T., 2012. One-stage and two-stage DEA estimation of the effects of contextual variables. Eur. J. Oper. Res. 220 (2), 559–570.

Johnson, A.L., Kuosmanen, T., 2014. An introduction to CNLS and StoNED methods for efficiency analysis: computational aspects and formulations. In: Ray, S., Kumbhakar, S., Dua, P. (Eds.), Benchmarking for Performance Evaluation: A Frontier Approach. Springer.

Klepper, G., Petersen, S., 2006. Marginal abatement cost curves in general equilibrium: the influence of world energy prices. Resour. Energy Econ. 28, 1–23.

Kuosmanen, T., 2008. Representation theorem for convex nonparametric least squares. Econ. J. 11, 308–325.

Kuosmanen, T., Fosgerau, M., 2009. Neoclassical versus frontier production models? Testing for the skewness of regression residuals. Scand. J. Econ. 2, 351–367.

Kuosmanen, T., Johnson, A.L., 2010. Data envelopment analysis as nonparametric least squares regression. Oper. Res. 58 (1), 149–160.

Kuosmanen, T., Kortelainen, M., 2012. Stochastic non-smooth envelopment of data: semi-parametric frontier estimation subject to shape constraints. J. Prod. Anal. 38 (1), 11–28.

Kuosmanen, T., Johnson, A.L., Saastamoinen, A., 2014. Stochastic nonparametric approach to efficiency analysis: a unified framework. In: Zhu, J. (Ed.), Handbook on Data Envelopment Analysis vol. 2. Springer.

Lee, C.-Y., Johnson, A.L., Moreno-Centeno, E., Kuosmanen, T., 2013. A more efficient algorithm for convex nonparametric least squares. Eur. J. Oper. Res. 227 (2), 391–400.

Mekaroonreung, M., Johnson, A.L., 2012. Estimating the shadow prices of SO_2 and NO_x for U.S. coal power plants: a convex nonparametric least squares approach. Energy Econ. 34 (3), 723–732.

Milliman, S.R., Prince, R., 1989. Firm incentives to promote technological change in pollution control. J. Environ. Econ. Manag. 17, 247–265.

Pasurka, C.A., 2006. Decomposing electric power plant emissions within a joint production framework. Energy Econ. 28, 26–43.

Porter, M.E., van der Linde, C., 1995. Toward a new conception of the environment–competitiveness relationship. J. Econ. Perspect. 9, 97–118.

Ray, S.C., Desli, E., 1997. Productivity growth, technical progress and efficiency change in industrialized countries: comment. Am. Econ. Rev. 87, 1033–1039.

Ray, S.C., Mukherjee, K., 1996. Decomposition of the Fisher ideal index of productivity: a non-parametric dual analysis of US airlines data. Econ. J. 106, 1659–1678.

Rosen, D., Schaffnit, C., Paradi, J.C., 1998. Marginal rates and two-dimensional level curves in DEA. J. Prod. Anal. 9, 205–232.

Rosendahl, K.E., 2004. Cost-effective environmental policy: implications of induced technological change. J. Environ. Econ. Manag. 48, 1099–1121.

Shephard, R.W., 1970. Theory of Cost and Production Functions. Princeton University Press. Pp. xi, Princeton 308.

Shestalova, V., 2003. Sequential Malmquist indices of productivity growth: an application to OECD industrial activities. J. Prod. Anal. 19, 211–226.

Solow, R.M., 1956. A contribution to the theory of economic growth. Q. J. Econ. 70, 65–94.

Solow, R.M., 1957. Technical change and the aggregate production function. Rev. Econ. Stat. 39, 312–320.

Tulkens, H., VandenEeckaut, P., 1995. Non-parametric efficiency, progress and regress measures for panel data: methodological aspects. Eur. J. Oper. Res. 80, 474–499.

Vijay, S., DeCarolis, J.F., Srivastava, R.K., 2010. A bottom-up method to develop pollution abatement cost curves for coal-fired utility boilers. Energy Policy 38, 2255–2261.