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Directional shadow price estimation of CO_2, SO_2 and NO_x in the United States coal power industry 1990–2010

Chia-Yen Lee [a,b,*], Peng Zhou [c]

[a] Institute of Manufacturing Information and Systems, National Cheng Kung University, Tainan City 701, Taiwan
[b] Research Center for Energy Technology and Strategy, National Cheng Kung University, Tainan City 701, Taiwan
[c] College of Economics and Management, Nanjing University of Aeronautics and Astronautics, 29 Jiangjun Avenue, Nanjing 211106, China

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ABSTRACT

Shadow prices, also termed marginal abatement costs, provide valuable guidelines to support environmental regulatory policies for CO_2, SO_2 and NO_x, the key contributors to climate change. This paper complements the existing models and describes a directional marginal productivity (DMP) approach to estimate directional shadow prices (DSPs) which present substitutability among three emissions and are jointly estimated. We apply the method to a case study of CO_2, SO_2 and NO_x produced by coal power plants operating between 1990 and 2010 in the United States. We find that DSP shows 1.1 times the maximal shadow prices estimated in the current literature. We conclude that estimating the shadow prices of each by-product separately may lead to an overestimation of the marginal productivity and an underestimation of the shadow prices.

1. Introduction

The challenges posed by climate change require large reductions of global carbon dioxide (CO_2) emissions, of which electricity and heat generation account for over 40%. Currently, a majority of electricity is still generated through burning coal, with the share increasing from 65% in 1990 to 72% in 2012 in the world (IEA, 2014). In addition to CO_2 emissions, coal-fired electricity generation also produces undesirable air pollutants such as sulfur oxide (SO_2) and nitrogen oxide (NO_x). In the United States (US), power plants generated around 77% of acid gases (e.g., hydrogen sulfide and CO_2), 60% of SO_2 and 13% of NO_x in 2010 (EPA, 2012a). Coal-fired electricity generation accounted for 44.8% of total electricity generation, which contributed to 78.4% of CO_2, 91.9% of SO_2, and 74.0% of NO_x among all power sectors (EIA, 2011). The federal Environmental Protection Agency (EPA) regulates pollution under the federal Clean Air Act (CAA) Amendments. In 2011, EPA released new environmental regulations which asked coal power plants to reduce emissions of 84 toxic chemical levels within four years (EPA, 2011). Around 1400 coal and oil-fired electric generating units (EGUs) at 600 power plants in US were covered under the new standards.

Recently, three major regulatory provisions — Mercury Air Toxics Standards (MATS), Cross-state Air Pollution Rules (CSAPR), and Clean Power Plan (CPP), were implemented to US coal-fired power plants. In 2011, EPA finalized MATS and CSAPR environmental regulations aiming at curbing air pollution from the electricity sector. MATS targeted for reducing the emissions of hazardous air pollutants, such as mercury and acid gases, from coal- and oil-fired power plants. The aim of CSAPR was to reduce SO_2, NO_x and ozone emissions that are crossing state lines from power units in the Eastern Interconnection primarily. In 2014, CPP was proposed to limit on CO_2 produced by both new and existing power plants. The overall goal is to achieve a 30% cut from the 2005 emissions by 2030, with an interim target of 25% on average between 2020 and 2029. More recently, EPA's proposal, "New Source Performance Standards", mandates a maximum of 1000 lb of CO_2 per MWh of electricity produced by new plants.

Emission trading is a widely accepted economic solution to environmental externalities, e.g., the by-products of coal power plants. The mechanism of emission trading is based on Coase's assertion (Coase,

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[*] Corresponding author at: Institute of Manufacturing Information and Systems, National Cheng Kung University, Tainan City 701, Taiwan. Tel.: +886 936 175488.

E-mail addresses: cylee@mail.ncku.edu.tw (C.-Y. Lee), cemzp@nuaa.edu.cn (P. Zhou).

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1960) that if trading in an externality and absent a transaction cost, bargaining will lead to an efficient outcome regardless of the initial allocation of property rights trading. Following his work, Dales (1968) proposed the conceptual model of an emission trading market with respect to a specific pollutant. Given the marginal abatement cost (MAC) curve and the marginal damages curve, the market would achieve equilibrium in the presence of externalities. Emission trading builds up the market incentive and achieves cost effectiveness, i.e., the benefits obtained from trading between parties will be larger than the benefit generated by individual emission reduction (Montgomery, 1972; Tietenberg, 1985). A few recent studies, however, claim that only considering the MAC of emission reduction may underestimate the damages to the national economy. Instead, they suggest considering the change of gross domestic product (GDP) when reducing the pollution via MAC (Klepper and Peterson, 2006; Kuik et al., 2009; Stankevicitue et al., 2008).

Estimating the MAC of pollutants provides valuable information to policy makers for devising and improving the operating rules of emission trading (Zhou et al., 2015). While there are different methods for estimating MAC, the shadow price of CO_2 may be used as a reference value to the allowance price in the emission trading market (Lee et al., 2002). The shadow price of undesirable output is derived from the market price of desirable output by using distance function and duality theory, and the distance function could be estimated by parametric or nonparametric approaches (Zhou et al., 2014).

In application, the parametric method is more commonly used because the specified production function is differentiable everywhere. Färe et al. (1993) first employed an output distance function with the translog functional form to estimate the shadow prices of four pollutants generated by pulp and paper mills in Michigan and Wisconsin in 1976. Coggins and Swinton (1996), who adopted the same approach to estimating the SO_2 shadow price of Wisconsin coal-burning power plants in 1990–1992. Färe et al. (2005) used a quadratic directional distance function (DDF) to estimate the shadow price of SO_2 for US electric utilities in 1993 and 1997. Harkness (2006) used the translog functional form to estimate CO_2 shadow prices in the US electric utility industry. Marklund and Samakovlis (2007) used DDF to estimate the MACs of CO_2 emissions for the EU member states in 1990–2000. Rezek and Campbell (2007) used ordinary least squares and generalized maximum entropy estimators to estimate the shadow prices of CO_2, SO_2, NO_x and mercury of 260 US electric power plants. Gupta (2006), Park and Lim (2009) and Matsushita and Yamane (2012) estimated the MAC of CO_2 in the electric power sectors of India, Korea, and Japan, respectively.

The nonparametric method, e.g., data envelopment analysis (DEA), have also been used to estimate production technology and the shadow prices of undesirable outputs. Boyd et al. (1996) used DEA to estimate the efficient frontier and the MAC of SO_2 for 29 coal-burning utilities in the US electric power industry. Lee et al. (2002) showed that the shadow price of a pollutant was the product of the inefficiency correction factor and the slope to the frontier.[1] Lee et al. (2014) developed a novel framework by integrating DDF/DEA with engineering-economic approach to estimating the shadow price of CO_2 in Korean power plants.[2] More recently, Zhou et al. (2015) conduct a comparison between nonparametric and parametric approaches in the context of estimating the shadow prices of CO_2 emissions in different industrial sectors.

A review of previous studies shows that DDF has received increasing attention in estimating the shadow prices of undesirable outputs. A notable fact is that the shadow price value is dependent on the direction projected to the frontier; that is, the shadow price is calculated based on the projection point on the frontier (Zhou et al., 2014). Coggins and Swinton (1996) derived relatively lower shadow price due to the choice of positive directions for both desirable and undesirable outputs towards the frontier, followed by Turner (1995) with a positive direction of desirable output, and then Boyd et al. (1996) with a positive direction of desirable output and a negative direction of undesirable output. Lee et al. (2002) gave the higher shadow price due to negative directions of both desirable and undesirable outputs. Clearly, the pre-determined direction projected to the frontier affects the shadow price estimation. A question immediately comes out: how to determine an appropriate direction? One purpose of this paper is to introduce a two-stage benchmarking technique to determine the directional vector: narrows down the infinite possible vectors into two alternatives in the first stage and derives the better one in the second stage (see Section 4.2).

In addition, we also find that most previous studies estimated the shadow prices of individual undesirable outputs separately. For instance, the equation $p_b = p_y(\frac{\partial \overrightarrow{D}_O(x,y,b;g^y,g^b)}{\partial b} / \frac{\partial \overrightarrow{D}_O(x,y,b;g^y,g^b)}{\partial y})$ is often used to estimate the shadow price, where p_b is the shadow price of pollutant b, p_y is the price of desirable output y and $\overrightarrow{D}_O(x, y, b; g^y, g^b)$ is the directional output distance function (Färe et al., 2005; Lee et al., 2002). This equation, which takes derivatives with respect to one specific undesirable output to estimate its shadow price,[3] implicitly assumes that a firm can generate only one type of pollutant at a time when increasing one extra unit of input. That is, estimating the shadow price of SO_2 is independent of estimating the shadow price of NO_x. In reality, the production process generates multiple undesirable outputs simultaneously when producing desirable outputs, e.g., burning 1 ton of coal emits around 1.46 to 2.57 tons of CO_2, 0.02 tons of SO_2 and 0.0045 to 0.0077 tons of NO_x (Albina and Themelis, 2003; EIIP, 2001; Radovic, 1997).[4] Thus, estimating shadow prices separately may lead to an overestimation of marginal productivity and an underestimation of shadow price. To overcome this issue, in this paper we propose a generalized directional marginal productivity (DMP) estimation of multiple outputs. We apply the proposed approach to estimating the directional shadow prices (DSP) of CO_2, SO_2 and NO_x given a prior-determined direction in a case study of US coal-fired power plants between 1990 and 2010. With the direction derived from our two-stage technique, the underestimation of shadow prices resulting from the use of separate marginal productivity estimation could be corrected.

The remainder of this paper is organized as follows. Section 2 introduces the DMP estimation. Section 3 develops the directional shadow prices (DSP) estimation of pollutants. Section 4 describes the empirical case study of the US coal power industry to estimate the DSPs of CO_2, SO_2 and NO_x. Section 5 concludes.

2. Directional marginal productivity via directional distance function

Marginal productivity (MP) represents the extra output generated by one more unit of an input. Given a specific direction, DMP represents

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[1] The inefficiency correction factor is the inefficiency ratio between desirable and undesirable outputs, which maps an inefficient point to the corresponding point on the production frontier.

[2] Despite the applicability of DEA in estimating shadow price, the DEA estimator is sensitive to outliers and the shadow price values equal to zero are quite common. Thus, Kuosmanen (2008) proposed a convex nonparametric least squares (CNLS) approach by integrating the merits of both parametric and nonparametric approaches. Kuosmanen and Johnson (2010) showed that DEA is a special case of CNLS with sign constraints on error terms. Mekaroonreung and Johnson (2012) used CNLS with random noise to estimate the shadow prices of SO_2 and NO_x in US bituminous coal power plants.

[3] The derivative can be obtained from the dual variable of output constraints in DEA (Lee et al., 2002) or the parameterization of the distance function (Färe et al., 2005).

[4] The components of coal directly affect the pollutant generation. Here, on average, 1 ton of coal-burning generates 1.4613 (39.85% carbon in a high ash coal) to 2.57 (70% carbon in bituminous coal) tons of CO_2, 0.02 tons of SO_2 (about 1% sulfur), and 0.0045 to 0.0077 tons of NO_x (about 1% nitrogen). The substantial emissions vary and depend on the sulfur content of the coal.