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Statistical inference in efficient production with bad inputs and outputs using latent prices and optimal directions

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ABSTRACT

Researchers employ the directional distance function (DDF) to estimate multiple-input and multiple-output production, firm inefficiency, and productivity growth. We relax restrictive assumptions by computing optimal directions subject to profit maximization and cost minimization, correct for the potential endogeneity of inputs and outputs, estimate latent prices for bad outputs, measure firms' responses to shadow prices rather than actual prices, and introduce an unobserved productivity term into the DDF. For an unbalanced panel of U.S. electric utilities, a model assuming profit-maximization outperforms one assuming cost-minimization, while lagged productivity and energy price have the greatest effect on productivity.

1. Introduction

As developed by Caves et al. (1982a, b), the distance function (DF) has been widely used to estimate radial representations of frontier production technologies where firms employ multiple good inputs to produce multiple good outputs. The distance from a production frontier is a measure of the firm's technical efficiency (TE). The change in this measure over time is efficiency change (EC), while the shift in the frontier over time is technical change (TC). The sum of these two measures is productivity change (PC). The DF is input- (output-) oriented if all inputs (outputs) are proportionally scaled down (up) to reach the production frontier while all outputs (inputs) are held constant.

One major shortcoming of the DF is that an entire set of inputs or an entire set of outputs must be scaled by the same factor. This becomes problematic when modeling the generation of electricity, since good inputs (capital, labor, and energy) and bad inputs (such as sulfur) produce good outputs (residential and industrial/commercial electricity) and bad outputs (pollutants). Using the DF, the researcher is not able to differentially credit the firm for simultaneously reducing bad outputs while increasing good outputs. In response, many authors have estimated an output DF and treated bad outputs like good inputs (holding both constant). However, this does not credit the firm for reducing bad outputs. Also, if bad inputs are consumed, no credit is given for their reduction.[1]

As an alternative, Chambers (1998) and Chambers et al. (1998) developed the directional distance function (DDF) which provides greater flexibility. It allows measurement of unique additive changes in each input and output through the calculation of different directions of movement for each to reach the production frontier. If non-zero directions are used to change only inputs (outputs), the DDF is input- (output-) oriented. When non-zero

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[1] A bad input like sulfur would be consumed only when it is organically bound to the coal and oil which are burned to generate electricity. To our knowledge, only Yaisawarng and Klein (1994) include fuel sulfur content and sulfur dioxide emissions in a study of electric utility production.

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directions are used to change all inputs and outputs, the DDF is technology-oriented.

Despite the greater flexibility of the DDF, researchers typically impose three overly-restrictive assumptions. First, the researcher usually specifies arbitrary directions of movement of current firm production toward the frontier to measure inefficiency.[2] However, different directions of movement toward the frontier will generate different measures of inefficiency. Three Data Envelopment Analysis (DEA) studies seek to avoid arbitrary assignment of directions by using linear programming methods to choose directions that *maximize* the measured distance (i.e., technical inefficiency) of the firm relative to a DDF. The first, by Färe et al. (2013), considers only good inputs and good outputs. The second, by Hampf and Krüger (2015), extends this analysis by including bad outputs. The stated goal of the third paper, by Zofio et al. (2013), is to compute optimal directions consistent with a firm's profit-maximization (PM) position on a DDF. They *assume* that firms are *currently* profit-maximizers and then measure the maximum distance from the current position. However, to measure the technology and productivity at the PM position, one must estimate the DDF jointly with the first-order conditions for PM. Since the latter are not included in their optimization model, the estimated directions cannot be consistent with PM. In this paper we estimate these conditions jointly with the DDF and compute directions consistent with PM, which we term "optimal-PM" directions.

Our approach follows Chambers (1998), who formulates a PM problem which includes a technology-oriented DDF (to measure the distance from the production frontier), and derives the first-order price equations for good inputs and outputs. In order to compute optimal-PM directions, Atkinson and Tsionas (2016) (AT) estimate the DDF jointly with the first-order price equations for only good inputs and good outputs, since the prices of bad outputs and bad inputs are missing. A complete set of utility-specific pollution permit prices (shadow prices for bad outputs) for the years of our sample data does not exist. As explained below, the prices of coal and oil include rebates for greater amounts of the bad input, sulfur. However, data is not publicly available to compute a hedonic price for sulfur.[3] We generalize AT by assuming a data generating process for latent prices of regulated bad outputs. These latent prices replace missing actual prices, allowing us to add the first-order price equations for regulated bad outputs to the AT system.

The second restrictive assumption of many DDF models is that all input and output quantities are exogenous. Highly-influential papers by Olley and Pakes (1996) (OP) and Levinsohn and Petrin (2003) (LP) consider the problem of estimating productivity in the presence of endogenous inputs using panel data. Both papers estimate a single-output Cobb–Douglas production function with a two-component random error term. The first component is firm- and time-varying productivity that is unobserved by the econometrician but observed, at least in part, by the firm. Since the firm takes productivity into account to some degree in choosing its inputs, endogeneity results. The second random component is an idiosyncratic error that is assumed to be uncorrelated with the explanatory variables and the productivity component. With the OP approach, the econometrician proxies for the unobserved productivity component with a potentially observable function. To obtain this function, OP first specify that investment is a monotonic function of productivity for a given level of capital and vintage. They then invert this function to obtain the productivity component as a proxy function of capital, investment, and vintage. Following OP, LP replace investment with materials and solve for the productivity component as a proxy function of capital, materials, and vintage. Productivity is assumed to follow a first-order Markov process. After discussing the modification of OP and LP by Ackerberg et al. (2015) (regarding when the firm chooses labor), Wooldridge (2009) provides the exact set of moment conditions required to identify each of these models, where instruments are subsets of current and lagged inputs. However, as Griliches and Mairesse (1998) stress, if the econometrician incorrectly specifies the productivity function, some degree of endogeneity remains. Both OP and LP recognize the possible invalidity of their instruments as well as the typical validity but unavailability of input and output prices as instruments.

In this paper, we avoid assuming that inputs are exogenous for electric utilities. In our sample, they vary input choice over time and these choices are arguably correlated with the idiosyncratic error term, when one misspecifies the proxy equation for productivity. This results in the endogeneity of input quantities. Such a result potentially applies to all input quantities with a cost-minimization (CM) model and to all input and output quantities with a PM model. Instead, we utilize the prices of good inputs and good outputs in our instrument set, since they are arguably exogenous. Utilities are price takers in input markets, since these markets are national (due to trans-continental oil and natural gas pipelines, trans-continental rail lines hauling coal and oil, and national mobility of labor and capital). Regulated utilities, which comprise the vast majority of our sample, face output prices that are set by regulatory commissions. The smaller number of restructured utilities face market-determined prices for good inputs and outputs.[4] Thus, for both types of firms, we employ input and output prices rather than input quantities in our instrument set.

The third restrictive assumption with all previous DDF models is that actual prices equal shadow (perceived) prices for the firm.[5] If the two sets of prices differ, the researcher must calculate optimal directions using shadow prices. Previous papers have developed the methodology to estimate shadow prices for profit, cost, and distance functions as summarized in Kumbhakar and Lovell (2000). However, our paper is the first to estimate shadow prices using a DDF and the first-order price equations from PM. We identify shadow prices by including input and firm-specific price inefficiency parameters in these equations. These parameters are estimated jointly with optimal-PM directions.

In addition, this paper is the first to estimate a model free of these three restrictive assumptions and, at the same time, explain the sources of firm productivity, without resorting to inconsistent two-step methods. Typically the two steps are: (1) regress output on a set of inputs and (2) regress the residuals on a set of explanatory variables that were omitted from the first step. The two sets of variables must be uncorrelated to avoid a potentially substantial bias.[6] We avoid this improbable requirement by employing an unrestricted profit function from which we derive productivity as an estimable function of lagged productivity, profits, prices of inputs and outputs, vintage, and time. We include this measure of productivity as an input in the DDF. This enables us to compute the partial elasticities of productivity with respect to its arguments and decompose productivity growth.

2 For example, assuming fixed directions, Färe et al. (2005) estimate an output DDF for electric utilities involving good inputs, a good output, and a bad output.

3 In the more typical industry study, prices of all inputs are missing and our methodology can be employed to estimate their first-order price equations having generated their estimated latent prices.

4 The goal of deregulation was to increase competition, yielding greater TE, productivity growth, and price efficiency. On the production frontier, the profit-maximizing firm achieves price efficiency when the price of each input equals the value of its marginal product. The cost-minimizing firm achieves allocative efficiency when ratios of input prices equal ratios of their marginal products.

5 Reasons for deviations of shadow from actual prices include tax write-offs, rate-of-return regulation, and constraints imposed by regulatory agencies or labor unions.

6 See Wang and Schmidt (2002) for details on Monte Carlo experiments indicating substantial potential bias in both steps.

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