Joint Production of Good and Bad Outputs with a Network Application

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Abstract

This paper surveys the literature on the joint production of good and bad outputs. Recently, material balance has arisen as an issue in this literature as a restriction on the technology, which we also address. We use our preferred specification of joint production technology and estimate the efficiency of U.S. electric utilities in a network setting. This network allows to specify two subtechnologies, one of which is an abatement technology.

1 Introduction

The evaluation of performance which accounts for joint production of good and bad outputs has become a small industry, for which we hope to provide a selective survey, which focuses on modeling and measurement issues. Also included is an application of our

[*]We would like to thank participants at the Verona EWEPA meetings special session on good modeling of bad outputs for their comments and Curtis Carlson for providing his capital stock data.

preferred model to estimation of efficiency of U.S. electric utilities in a network setting.

We begin by providing a simple framework for identifying desirable and undesirable outputs in a consumer preference framework, where more of good outputs is typically preferred to fewer, and fewer undesirable outputs are preferred to more. Turning to the producer side, we take an axiomatic approach. We begin with the premise that the good and bad outputs are jointly produced, i.e., the bad outputs are a byproduct of the production of good outputs. It is also assumed that we are interested in the case in which it is 'costly' to reduce the bad outputs. Recently there has been renewed concern with accounting for 'material balance' in the joint production case, which as generally formulated in the literature, imposes further restrictions on technology. We follow work by Rødseth (2011) and relax these restrictions to include abatement, in our case by specifying a network with two subtechnologies, one of which is an abatement subtechnology. Our application to electric utilities illustrates this approach and concludes.

2 Good vs Bad Outputs

We would like to have a systematic method of identifying desirable (good) and undesirable (bad) outputs. Our approach is to begin with preferences of a representative consumer. This consumer is assumed to have well-defined preferences $\succeq$ over two vectors of outputs, which we signify as $y \in \Re_+^M$ and $b \in \Re_+^J$. We say that y is a vector of good or desirable outputs if

$$y^{'} \geqq y \rightarrow (y^{'}, b) \succeq (y, b). \tag{1}$$

In words, our consumer prefers more of y to less of y as long as there is no more of b in the bundle.

We say that b is an undesirable or a bad output if

$$b^{'} \leqq b \rightarrow (y, b^{'}) \succeq (y, b), \tag{2}$$

and our consumer prefers less of b as long as y is held constant. We can illustrate our representative consumer's preferences for the simple case in which there is only one good output and only one bad output, as in Figure 1.[1]

The bundle (y, b) is on indifference curve I-I. The bundle $(y^{'}, b) \geqq (y, b)$ is preferred and thus is on a higher indifference curve II-II, due North of (y, b). Due West of (y, b)

[1] If the bad output does not affect consumers but rather another producer, we can think of the indifference curves as isoquants instead.

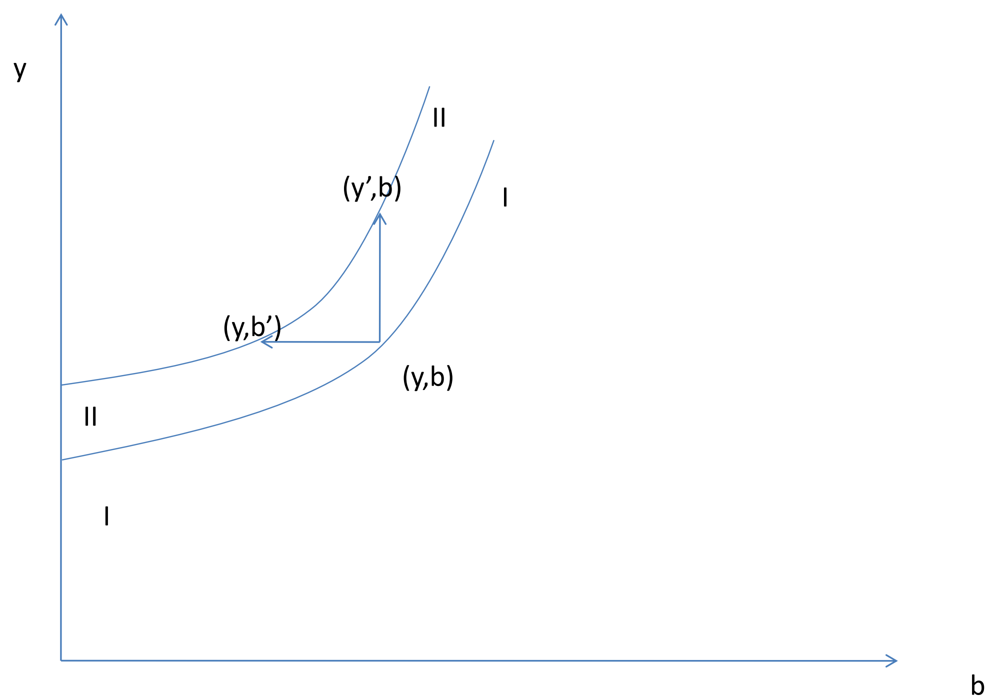

Figure 1: Preferences with Good and Bad Outputs

also on the higher indifference curve II-II is (y, b'), since $(y, b^{'}) \leqq (y, b)$. Thus classification of good and bad outputs is derived from consumer preferences.

Before we turn to specification of technology in the presence of these two types of outputs, we set the stage with an example of joint production of good and bad outputs from Anderson (1987, p. 5):

'For example, in making of potato chips, the principal material is potatoes. However, attached to these potatoes are the 'skins', which are usually not desired and are peeled off early in the production process. They are that part of the material input which is not usable.'[2]

3 The Production Technology

Again let $y \in \Re_+^M$ denote a vector of good outputs and $b \in \Re_+^J$ a vector of bad or undesirable outputs as determined by our representative consumer. We also introduce $x \in \Re_+^N$ to denote a vector of inputs. Then we can represent technology by its output sets[3]

$$P(x) \;=\; \{(y, b) : x \text{ can produce (y,b)}\}, x \in \Re_+^N. \tag{3}$$

We assume that $P(x)$ satisfies some conventional axioms, namely

P.1 $P(0) = 0$ which allows for inactivity.

P.2 $P(x)$ is closed.

P.3 $P(x)$ is bounded, which imposes scarcity.

P.4 $x^{'} \geqq x \rightarrow P(x^{'}) \supseteq P(x)$, strong or free disposability of inputs.

P.2 and P.3 together impose compactness on our output sets. P.4 implies that if inputs are increased (or not reduced), then the output set will not shrink. This property implies that inputs are not congesting output, an assumption that can be modified if appropriate.

The axioms itemized above on our technology are consistent with the traditional neoclassical model. In order to modify the traditional model so that it becomes an environmental production technology, we introduce additional assumptions specific to this

[2]Clearly, this predates the concept of stuffed potato skins.

[3]Much of this section has been presented elsewhere, see for example, Färe, Grosskopf, Noh and Weber (2005) and chapter 2 in Färe and Grosskopf (2004).

case.

One of the distinctive features of production in the presence of good and bad outputs is based on thermodynamics; as Baumgärtner et al (2001, p. 365) state

'...the production of wanted goods gives rise to additional unwanted outputs...'

i.e., bad outputs are essentially byproducts of production of good outputs. To model this condition, we introduce[4] the axiom of *null joint* production, i.e.,

P.5 if $(y, b) \in P(x)$, and $b = 0$ then $y = 0$.

This axiom states that if good and bad outputs are null joint, then if no bad outputs are produced, it is not possible to produce any good outputs—no fire without smoke. Or if good outputs are produced then some bad byproduct must also be produced.

In the traditional neoclassical specification of technology, it is generally assumed that all outputs are strongly disposable, i.e., in our case with good and bad outputs this would imply

P.6 if $(y, b) \in P(x)$ and $(y^{'}, b^{'}) \leqq (y, b)$ then $(y^{'}, b^{'}) \in P(x)$,

which as pointed out by Førsund (2009) would give us a

'...nonsensical result that zero bads can be achieved at no costs...'

Instead for our environmental technology we assume that the good and bad outputs are (together) *weakly disposable*, (Shephard (1970)),

P.7 if $(y, b) \in P(x)$ and $0 \leqq \theta \leqq 1$ then $(\theta y, \theta b) \in P(x)$.

Weak disposability is appropriate when we use Shephard's output distance function as our function representation of technology. If instead we represent the technology with a directional output distance function, *g-disposability* is required:

P.8 $y \in P(x), g \in \Re^M_+, g \neq 0, 0 \leqq \theta \leqq 1 \Rightarrow y + \theta g \in P(x)$.

Thus our particular output disposability assumption is associated with the function representation of the underlying set representation of technology, here $P(x)$. Since we will eventually be focusing on directional distance functions as our representation

[4] This axiom is from Shephard and Färe (1974).

of technology our base axioms are P.1-P.4 and P.8. In Section 5 we discuss Material Balance Models, which require further restrictions on our output sets.

We focus next on defining the specifications which are of empirical interest. We provide two specifications of a function representation of environmental output set $P(x)$ which satisfies axioms $P.1 - P.4$ and either $P.7$ or $P.8$. These include an Activity Analysis/Data Envelopment Analysis (DEA) specification and a parametric specification of the directional output distance function.

Beginning with the DEA specification, assume that we have data (x^k, y^k, b^k) on inputs and outputs for $k = 1, \ldots, K$ firms, farms or decision making units. We assume that these data satisfy the conditions proposed by Kemeny et al (1956), namely

$$\begin{aligned} &\sum_{m=1}^{M} y_{km} > 0, \quad k = 1, \ldots, K, \ \ \textstyle\sum_{k=1}^{K} y_{km} > 0, \quad m = 1, \ldots, M \\ &\sum_{n=1}^{N} x_{kn} > 0, \quad k = 1, \ldots, K, \ \ \textstyle\sum_{k=1}^{K} x_{kn} > 0, \quad n = 1, \ldots, N. \end{aligned} \tag{4}$$

In addition we require that

$$\sum_{j=1}^{J} b_{kj} > 0, k = 1, \ldots, K \quad \textstyle\sum_{k=1}^{K} b_{kj} > 0, \quad j = 1, \ldots, J \tag{5}$$

where the last set of inequalities ensure that technology satisfies null jointness. The first set of inequalities tells us that each firm produces some bad output and the second set states that each bad is produced by at least one firm.

All together these inequalities ensure that our DEA specification will satisfy our axioms, without requiring that inputs and outputs all be strictly positive. Given these conditions the DEA output set is then formulated as

$$\begin{aligned} P(x) = \{(y, b) : \ & \textstyle\sum_{k=1}^{K} z_k y_{km} \geqq y_m, & m = 1, \ldots, M \\ & \textstyle\sum_{k=1}^{K} z_k b_{kj} = b_j, & j = 1, \ldots, J \\ & \textstyle\sum_{k=1}^{K} z_k x_{kn} \leqq x_{kn} & n = 1, \ldots, N \\ & z_k \geqq 0, & k = 1, \ldots, K\}. \end{aligned} \tag{6}$$

This model satisfies P.1-P.4 and P.5. In addition it satisfies P.7 (weak disposability) and constant returns to scale, i.e.,

$$P(\lambda x) = \lambda P(x), \lambda \geqq 0. \tag{7}$$

We can use this activity analysis representation of technology as part of a DEA type estimator of the directional output distance function, defined as

$$\vec{D}_o(x, y, b; g_y, -g_b) \;=\; \max\{\beta : (y + \beta g_y, b - \beta g_b; g) \in P(x)\}, \tag{8}$$

where $g = (g_y, -g_b)$ is the directional vector which is the direction in which (y, b) is projected to the boundary of the output set $P(x)$. This can be estimated as the solution to a linear programming problem, with the objective which seeks to increase good outputs and decrease bad outputs as in (8) above and the constraints specified as the inequalities in (6) above. We note that the directional distance function signals efficiency when $\vec{D}_o(x, y, b; g_y, -g_b)$=0.

We can also parameterize the directional output distance function and estimate it using econometric techniques. In order to parameterize the function we make use of two useful conditions which it satisfies, the first

$$\vec{D}_o(x, y, b; g_y, -g_b) \geqq 0 \text{ if and only if } (y, b) \in P(x). \tag{9}$$

We refer to this condition as *representation*; for this condition to hold, outputs must be *g-disposable*. The directional output distance function also satisfies the *translation property*, denoted as

$$\vec{D}_o(x, y + \alpha g_y, b - \alpha g_b; g_y, -g_b) \;=\; \vec{D}_o(x, y, b; g_y, -g_b) - \alpha, \alpha \geqq 0. \tag{10}$$

The translation property is critical in the parameterization of the distance function. It together with the assumption that it can be approximated as a generalized quadratic form[5] implies that $\vec{D}_o(x, y, b; g_y, -g_b)$ should be parameterized using a quadratic functional form, eg.,[6]

$$\begin{aligned}
\vec{D}_o(x, y, b; 1, -1) \;=\;& \alpha_o + \sum_{n=1}^{N} \alpha_n x_n + \sum_{m=1}^{M} \beta_m y_m \\
+\;& \sum_{j=1}^{J} \gamma_j b_j + 1/2 \sum_{n=1}^{N} \sum_{n'=1}^{N} \alpha_{n,n'} x_n x_{n'} + 1/2 \sum_{m=1}^{M} \sum_{m'=1}^{M} \beta_{mm'} y_m y_{m'} \\
+\;& 1/2 \sum_{j=1}^{J} \sum_{j'=1}^{J} \gamma_{jj'} b_j b_{j'} + \sum_{n=1}^{N} \sum_{j=1}^{J} \nu_n x_n b_j + \sum_{m=1}^{M} \sum_{j=1}^{J} \mu_{mj} y_m b_j
\end{aligned} \tag{11}$$

[5]A function is generalized quadratic (here in two variables) if it takes the form $\Upsilon^{-1}(F(q_1, q_2)) = \alpha_o + \sum_{i=1}^{2} \alpha_i h(q_i) + \sum_{i=1}^{2} \sum_{j=1}^{2} \alpha_{ij} h(q_i) h(q_j), see Chambers (1988)$.

[6]See Färe, et al (2010).

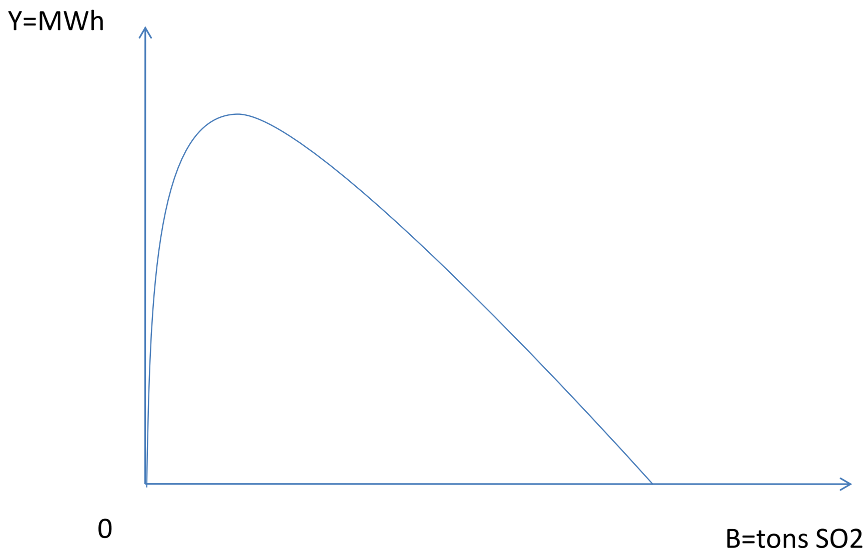

Figure 2: Typical Output Set

$$+ \sum_{n=1}^{N} \sum_{m=1}^{M} \delta_{nm} x_n y_m.$$

This could be estimated as a deterministic frontier as in Aigner and Chu (1968), which is a fairly simple linear or quadratic programming problem, or as a stochastic frontier problem.

4 Equilibrium

Using data from U.S. coal-fired electric utilities, Färe, et al (2005) estimated a quadratic directional output distance function as representation of the environmental output sets discussed earlier. The shape of the output sets from these estimates are illustrated in Figure 2.

Integrating this shape of an output set with the preferences from Section 2 yields

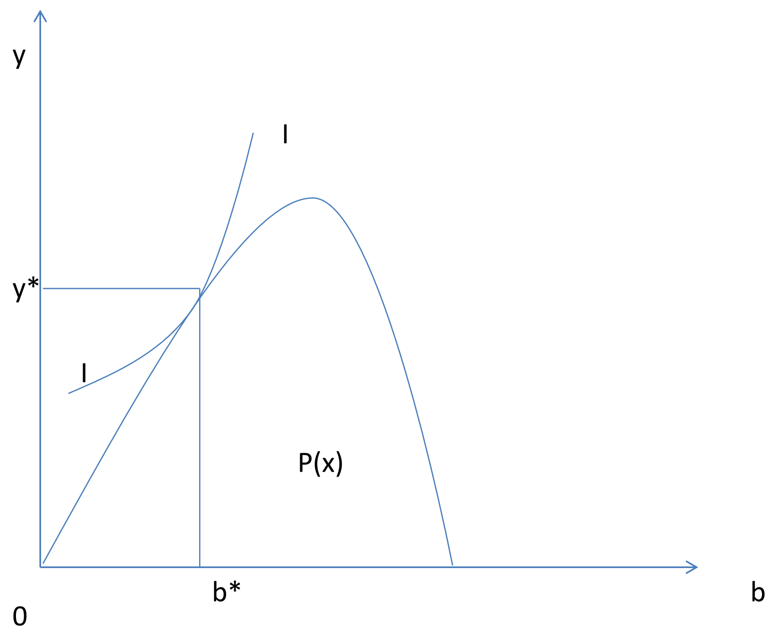

Figure 3: Equilibrium Production of Good and Bad Outputs

an equilibrium allocation of good and bad outputs, as in Figure 3, for the simple single good, single bad output case.

In Figure 3, the 'maximal' feasible utility level is achieved at (y^*, b^*) where the indifference curve I-I is tangent to the boundary of the output set $P(x)$. This also identifies the optimal tradeoff between good and bad outputs.

This tangency between the marginal rate of substitution and marginal rate of transformation can be used to estimate the 'price' of the bad output. The slope of the separating hyperplane between the indifference curve and the output set can be expressed as a price ratio between the good (p_{y_m}) and the bad outputs (p_{b_j}). As a tangent to $P(x)$, this may also be expressed as the ratio of derivatives of the directional output distance function, i.e.,[7]

[7]We are assuming here that those derivatives exist. For a more general case, see Chambers and Färe

$$\frac{p_{b_j}}{p_{y_m}} = \frac{\partial \vec{D}_o(x, y, b; g_y, -g_b)}{\partial b_j} / \frac{\partial \vec{D}_o(x, y, b; g_y, -g_b)}{\partial y_m}. \tag{12}$$

Thus if the price of at least one of the good outputs is known, then given estimates of the directional distance function based on sample data on inputs, good and bad outputs, the price of bad outputs $j = 1, \ldots, J$ can be computed from the estimated distance function as

$$p_{b_j} = p_{y_m} \frac{\partial \vec{D}_o(x, y, b; g_y, -g_b)}{\partial b_j} / \frac{\partial \vec{D}_o(x, y, b; g_y, -g_b)}{\partial y_m}, j = 1, \ldots, J. \tag{13}$$

5 Material Balance Principle

Based on the first law of thermodynamics. i.e., matter can neither be created nor destroyed, Ayres and Kneese (1969) introduced the notion of material balance into economics. This principle has recently been used by economists in specifying pollution technologies to restrict the substitutability among inputs, good and bad outputs.[8]

The general approach is to associate between an input x_n and an output y_m an input emission factor r_n and a recuperation factor s_m which are then used to solve for the bad output b (assume for the moment that it is a scalar) as[9]

$$b = r_n x_n - s_m y_m. \tag{14}$$

Hence the material balance principle forms a convex cone in input-output space, thus restricting feasible production possibilities. (In our example $s_m = 0$ since sulfur is not part of the good output.)

In general this formulation of the material balance condition would also imply that weak disposability of outputs and g-disposability would be restricted or infeasible. To visualize the impact on feasible production imposed by the material balance constraint (MB), we combine (14) with our output set from Figure 2 above, see Figure 4.

The intersection between the material balance constraint and the technology $P(x)$ is the line segment AB. Clearly, very little economic analysis can be done under these constraints.

A possible 'fix' is suggested in Rödseth (2011), namely to allow for abatement, i.e., modify the material balance principle as stated above to hold as an inequality, i.e.

(2008).

[8]See Coelli et al (2007), Murty et al (2010) Førsund (2009) and Rødseth (2011) for examples.

[9]This particular specification is based on Rødseth (2011).

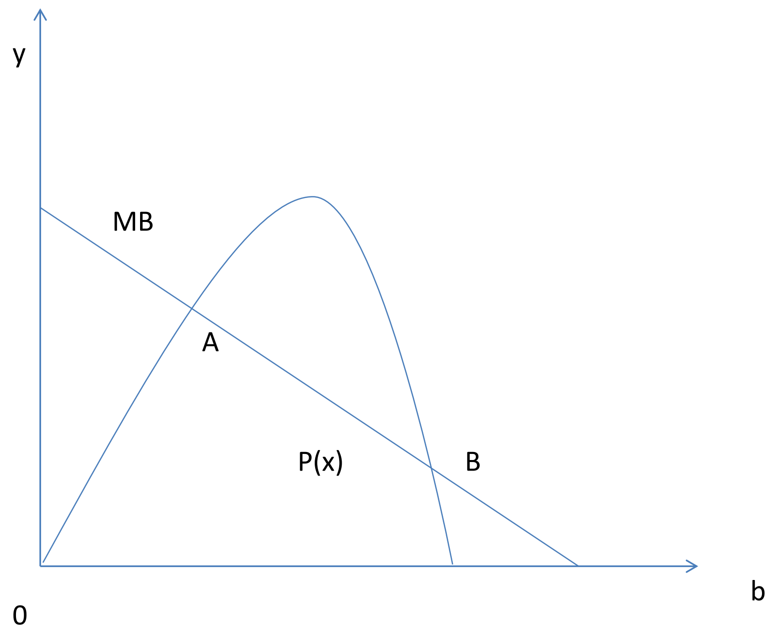

Figure 4: Technology and Material Balance

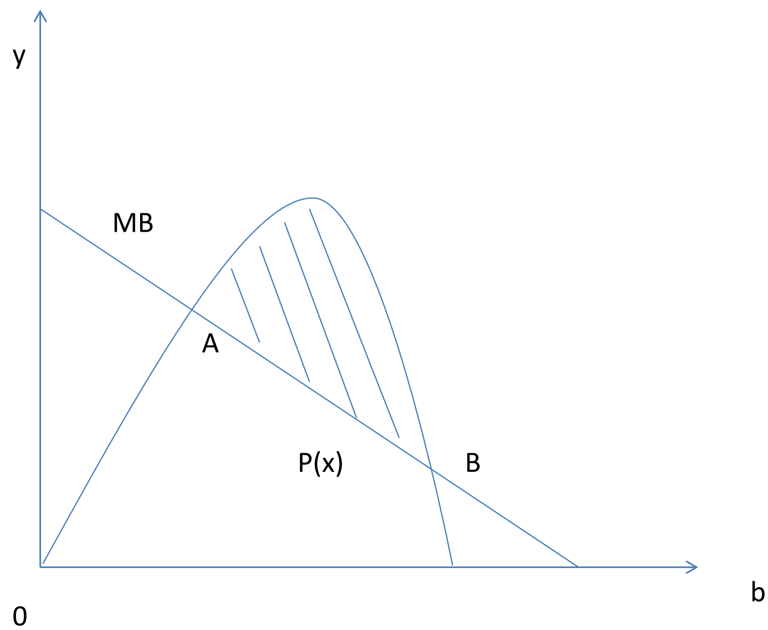

Figure 5: Technology, Material Balance with Abatement

$$b \geqq r_n x_n - s_m y_m. \tag{15}$$

If we allow for this relaxed constraint to admit abatement, we have Figure 5.

In this case the feasible economic region of the technology consists of the shaded part of the output set above AB. This accords more closely to observed data. This leads us into our Network Model in which we explicitly formulate an abatement subtechnology, which is then integrated into the overall production Network.

6 Modeling Good and Bad Outputs in a Network

Up to this point we have treated our production technology as something like a black box: inputs enter the technology and at the other end of the process, good and bad outputs are produced. Our assumption of weak disposability of outputs does not explicitly tell us how bad outputs may be reduced, just that with fixed inputs, reductions would require either lower overall production or diversion of some of the given inputs away from the production of goods to abate bad outputs, which would effectively reduce good output production as well.

Here we 'look inside the box' to explicitly introduce an abatement activity into the production process. Inside the box we specify subtechnologies, which are linked into a network. Our empirical example using data from U.S. coal-fired power plants, has two subtechnologies, namely the joint production of electricity and sulfur dioxide and the abatement subtechnology to reduce sulfur dioxide. We illustrate this setup in Figure 7 below.

The network consists of the two subtechnologies, P^1 and P^2. We also have what is referred to as a source entering the black box and a sink with final products exiting the black box. The source allocates the system exogenous inputs $x = (x^1 + x^2)$ into the two technologies and the sink sums up the final outputs (y^f, b^f). Within the black box, the good output y is either a final output y^f or an intermediate input y^i into P^2, so $y = (y^i + y^f)$. The abatement technology has (y^i, b^i) as intermediate inputs and x^2 as system exogenous input. Its output is the final bad output b^f. The sink forms the output bundle (y^f, b^f). The source adds up the subtechnologies' system exogenous inputs into $x = (x^1 + x^2)$.

The network technology may now be written as

$$P(x) \;=\; \{(y^f, b^f) : (y, b^i) \in P^1(x^1), y = y^f + y^i, b^f \in P^2(x^2, b^i, y^i), x \geqq (x^1 + x^2)\}. \quad (16)$$

'Optimizing' over $P(x)$, such as measuring efficiency or performance, yields optimal allocations of x into (x^1, x^2) and optimal allocation of y into y^i and y^f.

To estimate efficiency of the plants in our sample we apply a directional distance function (Chambers et al, (1998)) which expands the good outputs and contracts the bad. We choose the direction +1 for the good outputs and -1 for the bad outputs. This yields a straightforward interpretation of the resulting scores in terms of the original units of the good and bad outputs.[10]

We illustrate the directional output distance function in Figure 6, which is defined for the network technology as

$$\vec{D}_o(x, y^f + \beta \cdot 1, b^f - \beta \cdot 1) \in P(x)\}, \quad (17)$$

where $P(x)$ is defined above and the directional distance function is illustrated in the figure for the single good and single bad case. The output vector (y^f, b^f) at B is projected to the frontier of $P(x)$ in the (1,-1) direction, ending at A, given our direction vector

[10] This is a special case of Luenberger's shortage function, see eg., Luenberger (1995).

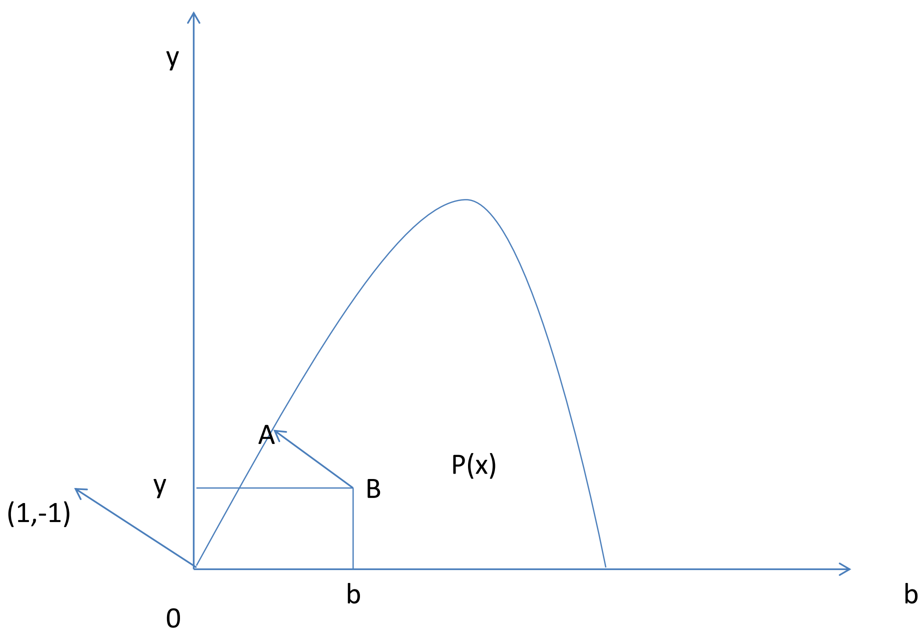

Figure 6: Directional Output Distance Function

$g = (1, -1)$. The distance β is the efficiency score and gives the number of additional units of good output and reductions in bad output required to move from B to A in that direction. The estimation of the efficiency scores are achieved within what we call the network DEA model.[11] We assume that there are $k' = 1, \ldots, K$ observations of coal-fired electric utilities with both subtechnologies, then the efficiency score for k' is the solution to the linear programming problem

$$
\begin{array}{rrl}
\max \beta & \text{s.t.} & \\
\text{SUBTECHNOLOGY 1:} & & \\
& \sum_{k=1}^{K} z_k^1 (y_k^i + y_k^f) \geqq & y^i + (y_{k'}^f + \beta \cdot 1) \\
& \sum_{k=1}^{K} z_k^1 b_k^i \;= & b^i \\
& \sum_{k=1}^{K} z_k^1 x_{kn}^1 \leqq & x_n^1, n = 1, \ldots, N \\
& z_k^1 \geqq 0, & k = 1, \ldots, K.
\end{array} \tag{18}
$$

$$
\begin{array}{rrl}
\text{SUBTECHNOLOGY 2:} & & \\
& \sum_{k=1}^{K} z_k^2 y_k^i \leqq & y^i \\
& \sum_{k=1}^{K} z_k^2 b_k^f \;= & b_{k'}^f - \beta \cdot 1 \\
& \sum_{k=1}^{K} z_k^1 b_k^i \leqq & b^i \\
& \sum_{k=1}^{K} z_k^2 x_{kn}^2 \leqq & x_n^2, n = 1, \ldots, N \\
& z_k^2 \geqq 0, & k = 1, \ldots, K
\end{array} \tag{19}
$$

$$
\begin{array}{rrl}
\text{SOURCE:} & & \\
& x_n^1 + x_n^2 \leqq & x_n, n = 1, \ldots, N.
\end{array} \tag{20}
$$

The individual subtechnologies have their own set of intensity variables, z_k^1 and $z_k^2, k = 1, \ldots, K$, respectively. These are restricted to be nonnegative which implies that we are allowing for constant returns to scale, in each subtechnology and for the network as a whole.

The two subtechnologies are connected by the use of y^i produced in subtechnology #1 which then becomes an input into subtechnology # 2. Similarly the bad output from subtechnology #1 becomes an input into subtechnology #2. In addition there is an indirect interaction between the subtechnologies through the source. We are solving for the intermediate good and bad outputs, y^i and b^i, respectively, as well as for the allocation of inputs to the subtechnologies, x^1 and x^2, respectively. The intensity variables and of course the value of β are also variables for which we solve. The 'data' are identified by

[11] See Färe and Grosskopf (2004) for details.

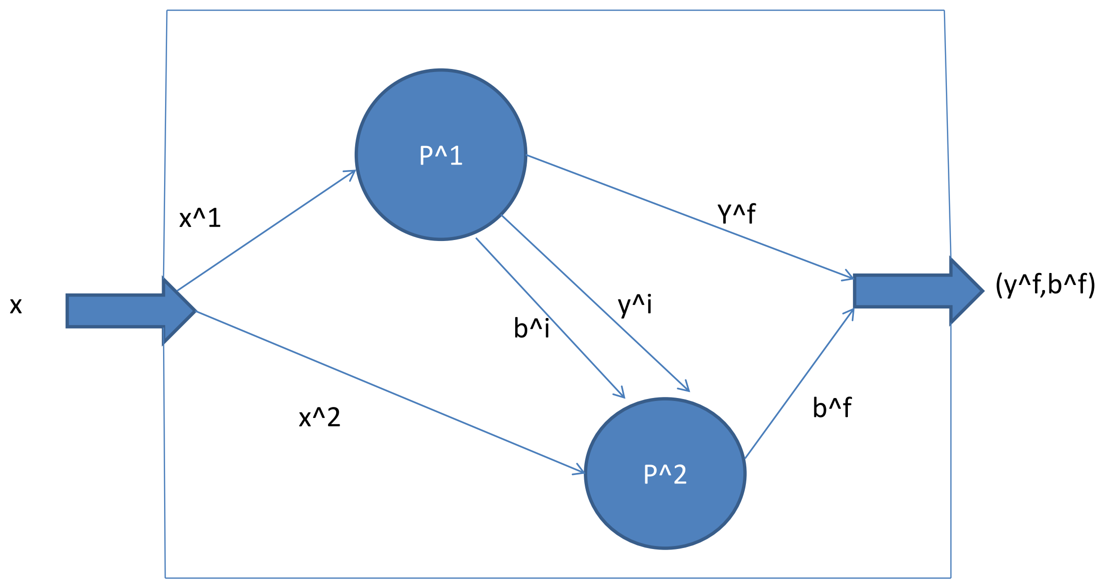

Figure 7: The Network Technology

their k subscripts and are generally on the left hand side of the inequality and equality constraints; the exceptions are the final good and bad outputs on the right hand side.

7 Network Model vs Joint Production Model

In this section we compare the above network model to the 'standard' joint production model.

The joint production model consists of one technology using inputs $x \in \Re_+^N$ (here the sum of x^1 and x^2) to produce good output y which is now the sum of y^f and y^i. The bad output b is now equal to b^i since we do not explicitly model the abatement process in this case, we just observe the total emitted bad outputs before abatement. Thus the activity analysis or DEA specification of our optimization problem is

$$
\begin{aligned}
\max_{z,\beta} \beta & & & (21)\\
s.t. & & & \\
\sum_{k=1}^{K} z_k y_k & \geqq & y_{k'} + \beta \cdot 1 & \\
\sum_{k=1}^{K} z_k b_{kj} & = & b_{k'j} - \beta \cdot 1, j = 1, \ldots, J & \\
\sum_{k=1}^{K} z_k x_{kn} & \leqq & x_{k'n}, n = 1, \ldots, N & \\
z_k & \geqq & 0, k = 1, \ldots, K. &
\end{aligned}
$$

In our empirical application we have only 14 observations in each period. In order to increase our degrees of freedom we create a grand or meta frontier for the joint production model as well as for the subtechnologies in the network model by pooling all of the data. So, for example, our output constraints in the joint production model will be modified to read

$$\sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t y_k^t \geqq y_{k'}^t, \tag{22}$$

and similarly for all of the input and output constraints in the network and the joint production models.

Our main interest is to see how the introduction of the network, which explicitly models the abatement process and allows for more flexibility, compares to the more restrictive joint production model. We anticipate that the greater flexibility of the network model will offer greater possibilities for improvement and therefore exhibit larger inefficiency scores than the joint production model.

8 Data

Data for coal-fired power plants from 2001 to 2005 are used to solve the linear programming problems in our basic joint production model (from (8) and (6)) and our network model (18) which includes abatement. The technology modeled in this study consists of one good output, net electrical generation—kilowatt hours (kWh), and one bad output—sulfur dioxide (SO2). The exogenous inputs consist of the capital stock, the number of employees, and the heat content (in Btu) of the coal, oil, and natural gas consumed at each plant. FERC Form 1 survey collects information on the cost of plant and equipment and the average number of employees for each electric power plant.[12]

The U.S. DOEs Form EIA-767 survey is the source of information about fuel consumption (Btu), and net generation of electricity (kilowatt hours). The U.S. EPA is our source for the net generation of SO2 (i.e., quantity of SO2 released into the atmosphere). Our panel consists of coal-fired power plants for 2001 to 2005. While the plants may consume coal, oil, or natural gas, in order to model a homogeneous production technology, coal must provide at least 95 percent of the Btu of fuels consumed by each plant. [13]

Details of how these data are constructed is included in the Appendix.

9 Results

The maximum level of technical inefficiency found by the joint production model is 0.09, while the maximum level of technical inefficiency for the network model is 1.6. The joint production and network models credit a producer for simultaneously expanding good output production and contracting bad output production. Both models calculate good output as the summation of net generation (electricity sold to final users) and the electricity used by flue gas desulfurization (FGD) systems. However the joint production model seeks to reduce gross SO2 emissions (i.e., emissions generated by the electric power plant prior to treatment by the FGD system), while the network model seeks to reduce net SO2 emissions (i.e., emissions released by the power plants after treatment by the FGD system). As a result, it is not surprising that the level of technical inefficiency found by the joint production model is substantially less than the technical inefficiency found by the network model.

[12] While the FERC Form 1 survey collects data on the historical cost of plant and equipment, it does not collect data on investment expenditures, the value of retired plant and equipment, or depreciation costs. As a result, we assume changes in the cost of plant and equipment reflect net investment (NI). Next, we convert the historical cost data into constant (1973) dollar values using the Handy-Whitman Index (HWI) (Whitman, Requardt & Associates, 2006). This is the same procedure employed by Yaisawarng and Klein (1994, p. 453, footnote 30) and Carlson et. al (2000, p. 1322). The net constant dollar capital stock (CS) for year n is calculated in the following manner: $CS_n = \sum_{t=1}^{n} \frac{NI_t}{HWI_t}$. In the first year of its operation, the net investment of a power plant is equivalent to the total value of its plant and equipment.

[13] Some plants are excluded due to their consumption of miscellaneous fuels: petroleum coke, blast furnace gas, coal-oil mixture, fuel oil #2, methanol, propane, wood and wood waste, refuse, bagasse and other nonwood waste. Although a number of plants consume fuels other than coal, petroleum, and natural gas, these miscellaneous fuels represent very small percentages of fuel consumption (in Btu). We decided to exclude a plant when its consumption of miscellaneous fuels represented more than 0.0001 percent of its total consumption of fuel (in Btu). For a plant whose consumption of miscellaneous fuels consumption represents less than 0.0001 percent of its fuel consumption, its consumption of miscellaneous fuels is ignored.

For both the joint production and network models, the level of inefficiency is dependent upon units of the good output, the units of the bad output, and the value of the g vector. Given our choice of direction vector as $g = (1, -1)$ our resulting scores will be in terms of the units of the goods and bads, respectively.

We summarize our results in the following diagrams. For each year, the scatter diagrams depict the technical inefficiency for each power plant found by the joint production and network models. For each year, the joint production model finds 3 to 9 of the 14 electric power plants with no technical inefficiency, while the network model finds only 0 to 2 plants with no technical inefficiency in each year. In addition, we use scatter diagrams for both the joint production and network models that include all observations from 2001-05.

In the network model, reassigning inputs from good output (i.e., electricity production) to pollution abatement results in a reduction of SO2 emissions (i.e., the bad output) at the cost of reduced good output production. Based on our raw data, we observe that the share of capital stock assigned to pollution abatement ranges from 7.1 to 27.5 percent, while the share of labor assigned to pollution abatement ranges from 1.9 to 41.1 percent. The share of total electricity output assigned to pollution abatement ranges from 0.1 to 2.9 percent. In terms of the output of the pollution abatement technology, net emissions as a share of gross emissions ranges from 4.9 to 63.2 percent.

We conclude that the network model does more closely approximate the technology of our electric utilities, and yields performance measures that provide more information to firms on how to improve their performance, both in terms of production of electricity and abatement of SO_2.

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10 Appendix

10.1 Derivation of Flue Gas Desulfurization Capital Stock

EIA-767 surveys are available for 1985 to the present. The EIA-767 survey collects data on the Installed Cost of FGD Unit, Excluding Land (thousand dollars) for the following categories: (a) Structure and Equipment, (b) Sludge transport and Disposal System and (c) Total (summation of lines a and b plus any other costs pertaining to the installation of the unit). In order to maximize the number of plants with FGD units in our sample, we use (c) Total when calculating the FGD capital stock.

The Federal Power Commission (FPC) Form 67 (the predecessor to the EIA-767 survey) results were published for 1969 - 1976. Although the FPC-67 and EIA-767 surveys were conducted between 1969 and 1984, the data on the installed cost of FGD systems have not survived. Hence, it is necessary to devise a strategy for approximating changes in the cost of FGD systems installed prior to 1965.

During this period, cost data were also collected by the EPAs Flue Gas Desulfurization Information System (FGDIS) and published in a series of reports entitled Utility FGD Survey and in the Energy Information Administrations annual report entitled Cost and Quality of Fuels. However, the FGDIS data are substantially different than the

EIA-767 data. As a result, we do not use the FGDIS data. Instead, we assume that prior to 1985 all FGD investment expenditures are undertaken in the year in which the FGD unit starts operation. Based on data for 1985-2005, this appears to be a reasonable approximation.

10.2 Derivation of FGD Electricity Consumption

The EIA-767 survey requests data on Electric Energy Consumption (kilowatt hours) for each FGD unit.

10.3 Derivation of FGD employment

The EIA-767 survey requests data for FGD O&M expenditures (in thousands of dollars) associated with Labor and Supervision. The next step is converting these data into the number of employees assigned to operate FGD units. Hence we need to calculate an average payroll cost per employee to derive the number of employees assigned to operate FGD units.

The FERC Form 1 collects information on the Distribution of Wages and Salaries associated with Electric power generation by private utilities (page 354). Unfortunately, the FERC Form 1 survey ceased collecting data on the number of Electric Department Employees (page 323) after 2001. Hence it is not possible to use these data to estimate the average cost per employee in the utility.

County Business Patterns provides data on number of employees and payroll for industries within states and counties (http://www.census.gov/epcd/cbp/download/cbpdownload.html). Dividing the payroll by the number of employees provides an estimate of the average cost of an employee for a NAICS industry in a given state. Dividing the EIA-767 value for FGD O&M expenditures for Labor and Supervision by the average cost of an employee (from the CBP data) yields an estimate of the number of employees at a power plant that are assigned to pollution abatement (i.e., operating the FGD units).

From 1998 to 2005, CBP data are reported using NAICS codes. The following NAICS industry classification codes are used in order of preference to assign wage rates to coal-fired electric power plants:

1. Fossil Fuel Electric Power Generation (NAICS 221112)
2. Electric Power Generation (NAICS 22111)
3. Electric Power Generation, Transmission and Distribution (NAICS 2211)

Due to confidentiality concerns, most counties in CBP do not report data for the detailed NAICS codes for electric power plants. As a result, we use CBP state data, and assume all power plants in a state are assigned the same wage and salary for a given year. If data are not available for a state, then we use values from a neighboring state.

Once the number of employees assigned to operate the FGD units is determined, this value is subtracted from total employment (from FERC Form 1) at the plant. The difference constitutes the number of employees assigned to generate electricity.

10.4 Derivation of Gross SO_2 Emissions

In order to identify the amount of SO_2 abated by an FGD system, it is necessary to compute the difference between potential (i.e., gross) SO_2 emissions and measured (i.e., net) SO_2 emissions. Hence, the challenge is developing an estimate of potential (i.e., gross) SO2 emissions for plants with FGD units. The EIA-767 provides information on the SO_2 content of coal and oil consumed by each plant. The 2004 Electric Power Annual (Energy Information Administration, U.S. Department of Energy, 2005, p. 74) reports SO_2 Uncontrolled Emission Factors for six different boiler type / firing configurations for different types of fuels. Starting in 2001, the EIA-767 fuel data provides detailed information on each type of fuel consumed. For example, prior to 2001 the EIA-767 would report data on Coal consumption. Starting with 2001, the fuel would be identified as bituminous or sub-bituminous.

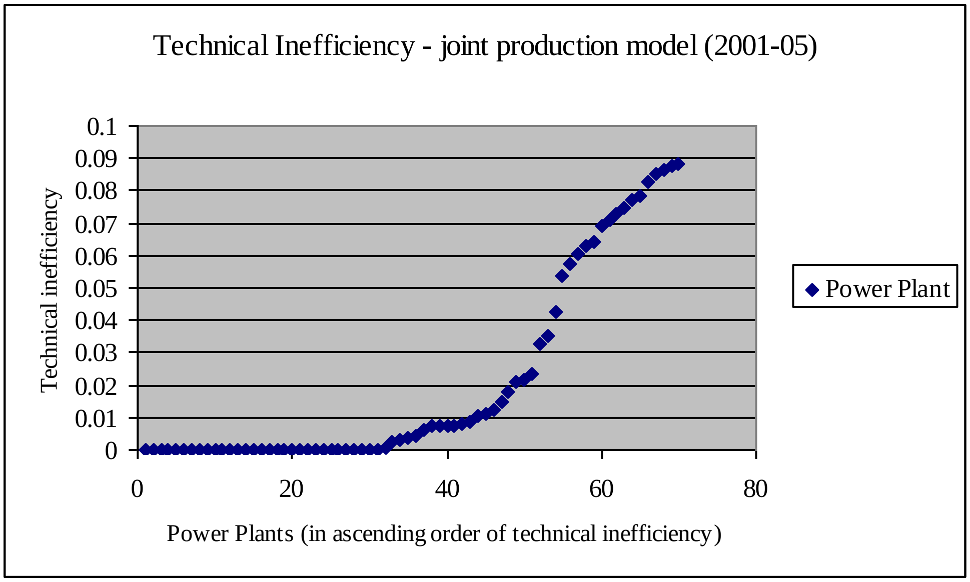
For each plant with an operational FGD unit, we take the product of the quantity of fuel consumed by each boiler of a plant, the sulfur content of the fuel consumed by the boiler, and the boilers uncontrolled SO_2 emission factor. This yields the quantity of uncontrolled SO_2 emissions (i.e., gross SO_2 emissions).

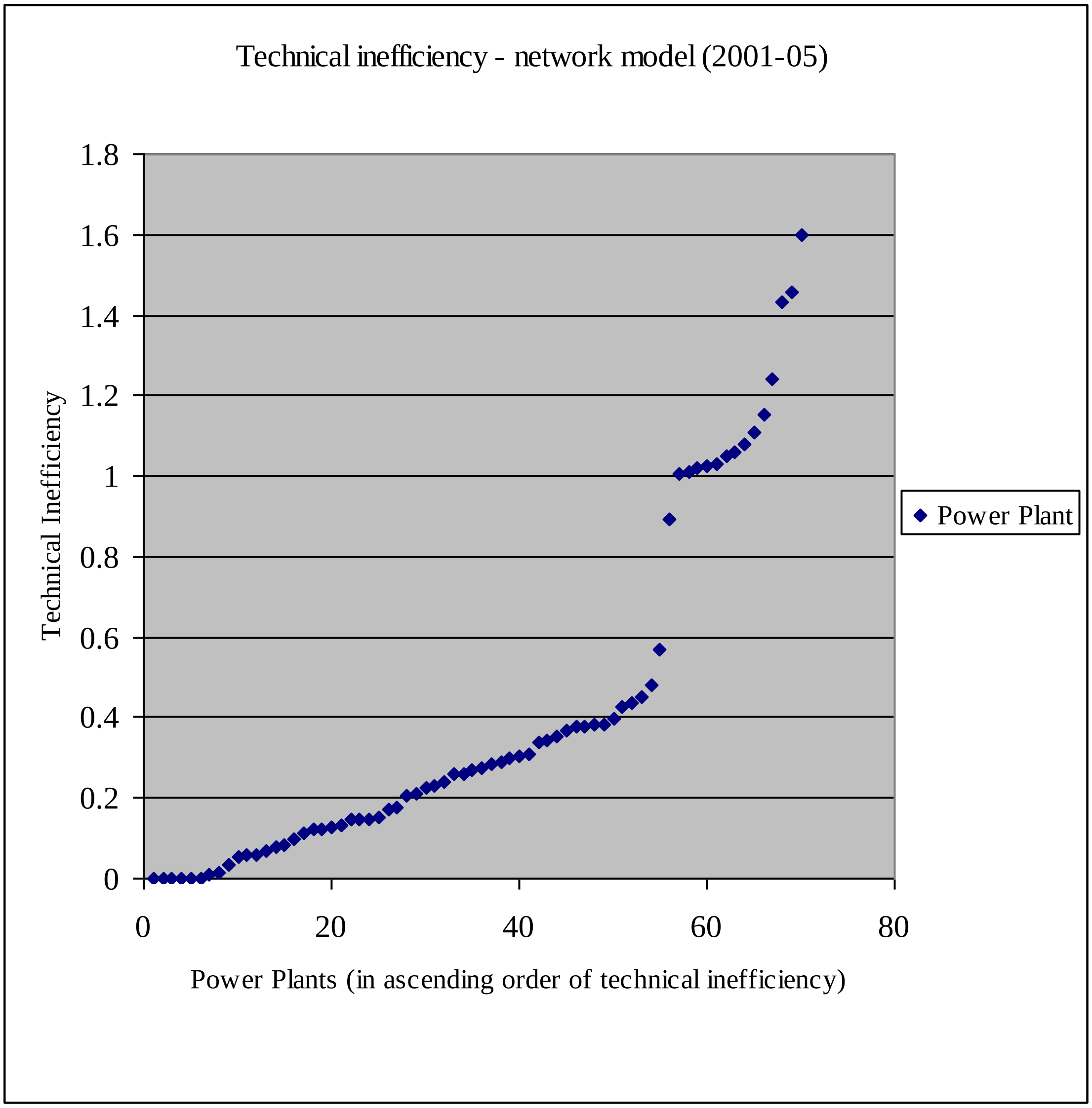
10.5 Sample

The EIA-767 survey was not conducted in 2006. Starting in 2007, Form EIA-860 and the Form EIA-923 collect most of the data formerly collected on the Form EIA-767.

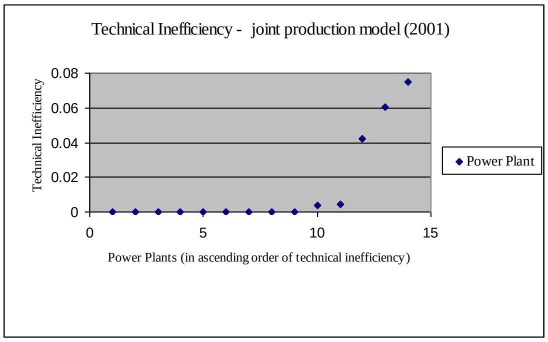
Some employment and historical cost of plant for (1) Structures and Improvements and (2) Equipment data are interpolated. Otherwise, if a plant did not report fuel consumption, net generation of electricity, or SO_2 emission data for a single year, the plant is not included in our sample.

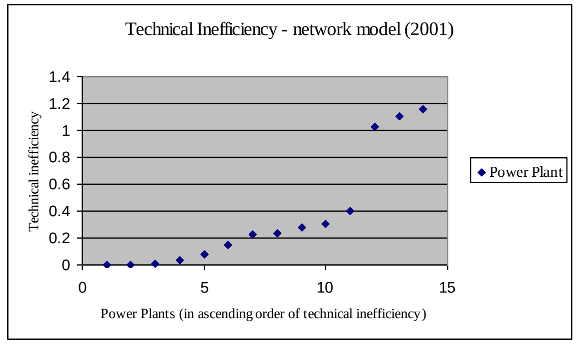
Given the availability of information to generate gross SO_2 emissions, our sample consists of observations from 2001-05. From our initial 2001-05 sample developed for a joint production model with 112 coal-fired electric power plants, we identified 35 plants with operational FGD units for at least one year from 2001-05. Of those 35 plants, it is necessary to remove 22 plants from our sample because either the FDG systems were not operating during the entire period or the plant failed to report one or more of the following pieces of information: (1) FGD electricity consumption, (2) FGD employment, or (3) FGD capital stock. If we included these plants we would be treating plants with operational FGD systems as if they had no installed FGD units. As a result, 14 of the 94 power plants in our sample have an operational FGD system during 2001-2005.


Technical Inefficiency - joint production model (2001-05)
Technical inefficiency
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
0
20
40
60
80
Power Plants (in ascending order of technical inefficiency)
Power Plant



Technical inefficiency - network model (2001-05)
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
Technical Inefficiency
0
20
40
60
80
Power Plants (in ascending order of technical inefficiency)
Power Plant


Technical Inefficiency - joint production model (2001)
Technical Inefficiency
Power Plants (in ascending order of technical inefficiency)
Power Plant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Power Plants (in ascending order of technical inefficiency)
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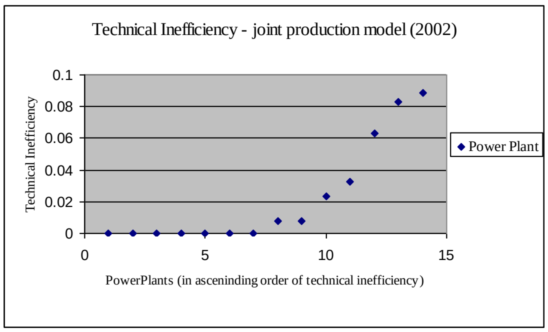
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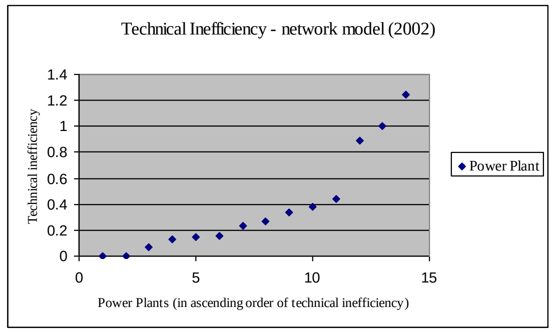
Technical Inefficiency - network model (2002)
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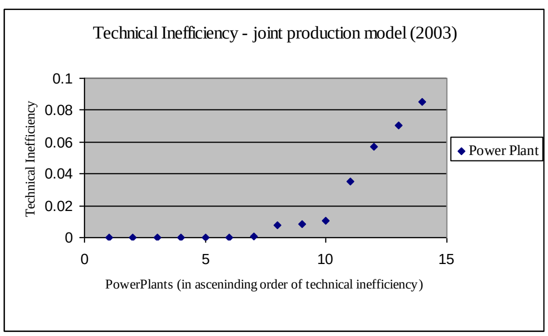
Power Plants (in ascending order of technical inefficiency)
Power Plant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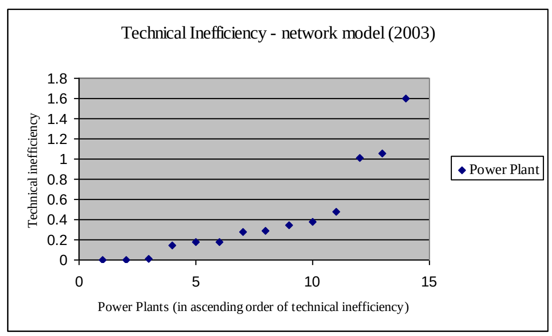
Technical Inefficiency - network model (2003)
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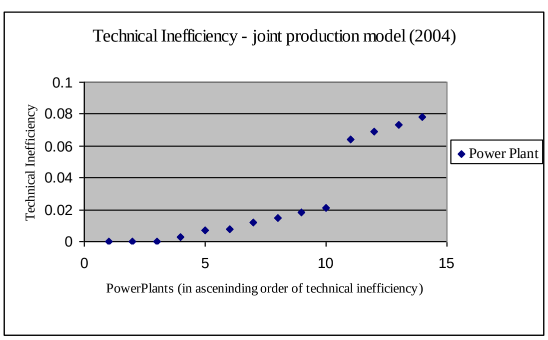
Power Plants (in ascending order of technical inefficiency)
Power Plant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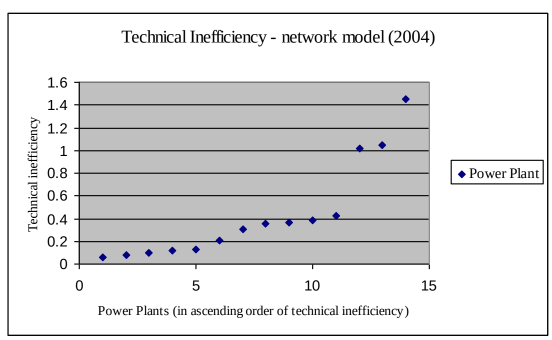
Technical Inefficiency - network model (2004)
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Power Plants (in ascending order of technical inefficiency)
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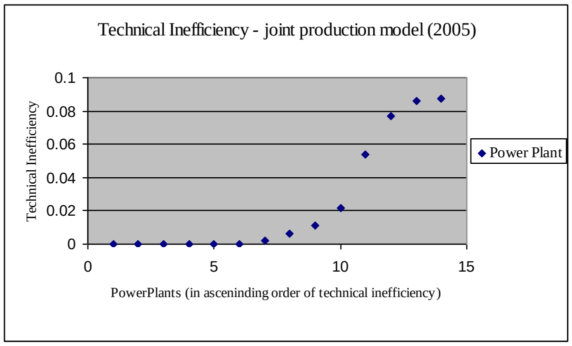
Technical Inefficiency - joint production model (2005)
Technical Inefficiency
0.1
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0.04
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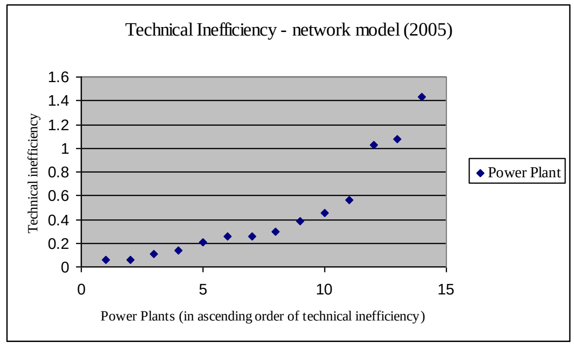
PowerPlants (in asceninding order of technical inefficiency)
Power Plant


Technical Inefficiency - network model (2005)
Technical inefficiency
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0
5
10
15
Power Plants (in ascending order of technical inefficiency)
Power Plant