ON DESIGNING AN EFFICIENT $\mathrm{CO_2}$ EMISSIONS CAP AND TRADE SYSTEM

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BACKGROUND

- Since the late 1960's, the U.S. federal government has:
  1. regulated nationwide an ever-expanding set of air pollutant emissions from fossil-fueled electricity generating facilities.
  2. proceeded piecemeal, pollutant by pollutant, to control TSP, SO_2, and NO_x.
  3. over time drastically ratcheted down the emission rates for each criteria pollutant, without consideration of emission rates of other such pollutants.

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  1. Supreme Court ruled USEPA has the authority to regulate $\mathrm{CO_2}$.
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- Again, $\mathrm{CO_2}$ control is treated as separable.
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- Example # 1: switching to low-sulfur (which is lower Btu) coal increases particulate, NO_x, and CO_2 emissions and reduces power output going into the grid
    1. The performance of the electrostatic precipitators used to capture particulates is enhanced by greater flue gas sulfur content.
    2. Low-sulfur coal produces less heat per unit of coal $\rightarrow$ more coal burned to produce a given amount of electricity.
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- Example # 2: Controls aimed specifically at CO_2 also exhibit this jointness.
  1. Amine-based technology is the currently favored technology to capture CO_2 at coal-fired power plants.
  2. Because amine-based sorbents absorb all acid gases, not just CO_2, SO_2 emissions may be well below allowable SO_2 emissions.
  3. This may cause SO_2 marginal control costs to greatly exceed marginal benefits.
  4. Moreover, this technology would consume roughly 25 percent of gross power plant output (Davison, 2007).

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- Example # 3: Shutting down old, dirty plants to meet the SO_2 cap:
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- Conclusion for Examples 1-3 :
    1. While utilities do not directly control $\mathrm{CO_2}$ emissions, We find considerable jointness across $\mathrm{SO_2}$, $\mathrm{NO_x}$, and $\mathrm{CO_2}$ emissions.
    2. This implies that the separability approach will not equate the marginal cost of controlling each pollutant within power plants and across plants.
- Additional implication: about 50% of states apply rate-of-return (ROR) regulation to electricity production and distribution.
    1. Fowlie (2009) finds that utilities in states with ROR regulation over-capitalize in $\mathrm{NO_x}$ pollution control equipment rather than fuel-switch.
    2. These concerns for $\mathrm{CO_2}$ scrubbers are magnified by an order of magnitude, since their costs are 10-fold or more than the costs of existing scrubbers.

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BASIC APPROACH

- In this paper, we examine the U.S. electricity industry
  1. the largest sector in terms of energy-related carbon dioxide emissions
  2. accounts for 41 percent of total emissions.
- We estimate for the electric utility industry:
  1. a multiple-input, multiple-output production function
  2. that produces good and bad outputs
  3. from good and bad inputs.
- We wish to estimate
  1. technical efficiency,
  2. allocative efficiency,
  3. productivity change,
  4. implicit prices of bad outputs
  5. **most importantly:** partial effects (jointness) among inputs and outputs.

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- The Conventional Steam-Electric Utility Industry produces:
  1. two good outputs– residential and industrial-commercial kilowatt hours (Kwh)
  2. the three bads: SO_2, CO_2, and NO_x.
- Using:
  1. one bad input, sulfur (S),
  2. four good inputs–fuel, production capital, pollution control capital, and labor.
- We wish to differentially credit utilities for
  1. reduction of bad inputs,
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DIRECTIONAL DISTANCE FUNCTION

- Let:
  1. $\mathbf{x}$ be good inputs
  2. $\tilde{\mathbf{x}}$ be bad inputs
  3. $\mathbf{y}$ be good outputs
  4. $\tilde{\mathbf{y}}$ be bad outputs

- Following Chambers et al. (1998), we define the technology directional distance function as

$$\overrightarrow{D}_T = \sup\{\beta : (\mathbf{x} - \beta\delta_x, \tilde{\mathbf{x}} - \beta\delta_{\tilde{x}}, \\ \mathbf{y} + \beta\delta_y, \tilde{\mathbf{y}} - \beta\delta_{\tilde{y}}) \in P\}. \quad (1)$$

- $P(\mathbf{x}, \tilde{\mathbf{x}})$ is the output set of goods and bads that can be produced with $(\mathbf{x}, \tilde{\mathbf{x}})$.
- The technology directional distance function decreases good inputs, bad inputs, and bad outputs in the direction $(-\delta_x, -\delta_{\tilde{x}}, -\delta_{\tilde{y}})$ and increases good output in the direction (δ_y) in order to move to the frontier of P.
- We assume maximization of shadow profits based on input and output quantities that the firm would like to produce if it could maximize profits. This allows for restrictions on inputs and outputs due to regulations.

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$$\overrightarrow{D}_T = \sup\{\beta : (\mathbf{x} - \beta\delta_x, \tilde{\mathbf{x}} - \beta\delta_{\tilde{x}}, \mathbf{y} + \beta\delta_y, \tilde{\mathbf{y}} - \beta\delta_{\tilde{y}}) \in P\}. \tag{1}$$

- $P(\mathbf{x}, \tilde{\mathbf{x}})$ is the output set of goods and bads that can be produced with $(\mathbf{x}, \tilde{\mathbf{x}})$.
- The technology directional distance function decreases good inputs, bad inputs, and bad outputs in the direction $(-\delta_x, -\delta_{\tilde{x}}, -\delta_{\tilde{y}})$ and increases good output in the direction (δ_y) in order to move to the frontier of P.
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- We impose three important properties of the technology directional distance function:
  1. non-negativity,
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y=good output
x=good input
b=bad output

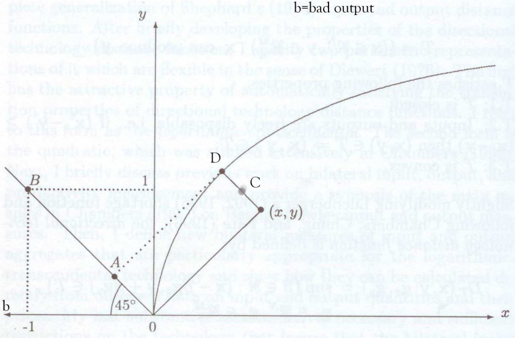

Figure 6.1 The Directional Technology Distance Function

- A two-sided error is appended to the quadratic form of the directional distance function:

$$\epsilon_{it} = (v_{it} - u_{it}), \tag{2}$$

1. a one-sided component, u_{it},
2. and a standard noise component, v_{it}, with zero mean.

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- The directional distance function is approximated using a quadratic function of input and output quantities.
- What direction to use?
  1. An environmentalist might believe that increasing good output is less important than reducing bad output. Hence, he might choose a directional vector of $(\mathbf{g}_y, \mathbf{g}_{\tilde{y}}) = (.85, -1)$ for good and bad outputs.
  2. A stockholder in a utility might believe the opposite and choose the vector $(\mathbf{g}_y, \mathbf{g}_{\tilde{y}}) = (1, -.85)$ instead.

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BAYESIAN IMPLEMETATION

- Due to the large number of estimated parameters and the need to impose monotonicity, we employ a Bayesian Generalized Method of Moments estimator with instruments, implemented with MCMC.
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DATA AND RESULTS

- Our sample is a balanced panel of 77 U.S. electric utilities from 1988-97.
- At the utility level, we employ the:
  1. Quantities of good outputs(Kwh) for residential and industrial/commercial users plus their prices,
  2. Bad outputs–$\mathrm{SO_2}$, $\mathrm{CO_2}$, and $\mathrm{NO_x}$. No prices.
  3. Bad input is S. We know total S burned. No price.
  4. The price and quantity of all good inputs: labor (L), capital for production (K_{prod}), capital for pollution control (K_{pol}), and energy for production (E).
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- Over time, $\mathrm{SO_2}$ emissions have fallen, but $\mathrm{CO_2}$ and $\mathrm{NO_x}$ emissions have risen.
- TC can logically decline, since emissions have risen.
- Examine four direction sets:

  1. direction set 1: $g_y = .85; g_{\tilde{\mathbf{y}}} = g_x = g_{\tilde{x}} = -1$
  2. direction set 2: $g_y = 1; g_{\tilde{\mathbf{y}}} = g_x = g_{\tilde{x}} = -.85$
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- For the last direction set, the posterior median technical efficiency rises over time from .61 in 1988 to .64 in 1997.
- For the last direction set, we observe slight allocative inefficiency:
  1. minor overuse of capital relative to labor
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PC, TC, and EC

- Productivity change (PC), technical change (TC), and efficiency change (EC) are defined as:

$$PC = TC + EC, \tag{3}$$

1. where TC is rate of outward movement of the frontier.
2. and EC is the rate by which firms catch up with the frontier.

- For the last direction set, PC is less than one percent and increases slightly over the sample period.
- TC is slightly negative early in the sample, but switches to small positive levels in later years.
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- Shadow prices of bad outputs do not exist outside of relatively thin markets for $\mathrm{SO_2}$ and $\mathrm{NO_x}$ emission permits.
- the price for $\mathrm{CO_2}$ is positive reflecting the fact that it is an unregulated pollutant.
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Total Derivatives:
Outputs wrt Outputs Using the implicit function theorem

- Reducing SO_2 does appear to cause a small increase in CO_2 for some firms with existing technology: median $dCO_2/dSO_2 = -.143$ with s.d.=.239.
- A reduction in NO_x reduces CO_2 substantially for most firms with existing technology: median $dCO_2/dNO_x = .738$ with s.d.=.258.
- A reduction in NO_x reduces SO_2 substantially for most firms with existing technology: median $dSO_2/dNO_x = 1.548$ with s.d.=1.318.
- The Industrial/Commercial and Residential output total derivative is almost eactly -1 as expected with very small s.d.=.024.

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Total Derivatives: Outputs wrt Inputs

- As expected the median total derivative $dSO_2/dS = 1.114$ with a s.d.=.89.
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CONCLUSIONS:

- In the short run, reductions in SO_2 are associated with increases in CO_2.
- In the long run, reductions in CO_2 due a CO_2 standard will also (assuming amine-based technology is employed) reduce SO_2 below the standard.
- Reducing NO_x causes a substantial reduction in CO_2 and SO_2 for most firms, due to improvements in production technology over the sample.
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GRACIAS!

Table 9: Total Derivatives–Outputs (by column) With Respect to Outputs (by rows)

$$Direction : g_y = 1, g_{\tilde{y}} = g_x = g_{\tilde{x}} = -1$$

	R	IC	SO_2	CO_2	NO_X
R	0.000 (0.000)	-1.076 (0.024)	0.398 (0.490)	0.232 (0.088)	-0.263 (0.124)
IC	-0.929 (0.020)	0.000 (0.000)	0.351 (0.464)	0.214 (0.082)	-0.239 (0.115)
SO_2	0.545 (0.953)	0.576 (1.003)	0.000 (0.000)	-0.143 (0.239)	0.267 (0.248)
CO_2	3.823 (1.257)	4.104 (1.377)	-1.495 (1.820)	0.000 (0.000)	1.139 (0.309)
NO_X	-2.844 (1.471)	-3.016 (1.567)	1.548 (1.318)	0.738 (0.258)	0.000 (0.000)

Table 10: Total Derivatives – Outputs (by rows) with respect to Inputs (by columns)

$$Direction : g_y = 1, g_{\tilde{y}} = g_x = g_{\tilde{x}} = -1$$

	R	IC	SO_2	CO_2	NO_X
K_{prod}	0.615	0.659	-0.258	-0.138	0.168
	(0.056)	(0.064)	(0.300)	(0.053)	(0.077)
L	0.726	0.770	-0.329	-0.162	0.195
	(0.048)	(0.054)	(0.362)	(0.061)	(0.091)
E	0.668	0.711	-0.251	-0.147	0.167
	(0.049)	(0.048)	(0.296)	(0.057)	(0.078)
K_{pol}	0.651	0.689	-0.322	-0.097	0.165
	(0.418)	(0.442)	(0.400)	(0.116)	(0.148)
S	-2.127	-2.235	1.114	0.473	-0.529
	(1.003)	(1.057)	(0.890)	(0.282)	(0.380)

Table 11: Total Derivatives – Inputs (by rows) with respect to Inputs (by columns)

$$Direction : g_y = 1, g_{\tilde{y}} = g_x = g_{\tilde{x}} = -1$$

	K_{prod}	L	E	K_{pol}	S
K_{prod}	0.000 (0.000)	-0.877 (0.083)	-0.845 (0.099)	-0.378 (0.167)	0.241 (0.106)
L	-1.117 (0.110)	0.000 (0.000)	-0.907 (0.089)	-0.443 (0.181)	0.289 (0.128)
E	-1.093 (0.130)	-1.040 (0.101)	0.000 (0.000)	-0.350 (0.164)	0.260 (0.113)
K_{pol}	-0.989 (0.613)	-0.920 (0.576)	-0.893 (0.615)	0.000 (0.000)	0.075 (0.098)
S	3.376 (1.622)	3.059 (1.422)	3.163 (1.503)	3.726 (2.555)	0.000 (0.000)