ON DESIGNING AN EFFICIENT CO_2 EMISSIONS CAP AND TRADE SYSTEM

Mark Agee   Scott E. Atkinson   Tom Crocker   Jon Williams

Department of Economics:
Penn State University Altoona, PA
University of Georgia Athens, GA
University of Wyoming Laramie, WY
University of Georgia Athens, GA

October 2012

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, $\mathrm{SO_2}$, and $\mathrm{NO_x}$.
    3. over time drastically ratcheted down the emission rates for each criteria pollutant, without consideration of emission rates of other such pollutants.

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, $\mathrm{SO_2}$, and $\mathrm{NO_x}$.
    3. over time drastically ratcheted down the emission rates for each criteria pollutant, without consideration of emission rates of other such pollutants.

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, $\mathrm{SO_2}$, and $\mathrm{NO_x}$.
  3. over time drastically ratcheted down the emission rates for each criteria pollutant, without consideration of emission rates of other such pollutants.

- Source-specific, technology-based emission standards initially were dominant regulatory tools.
- In the last two decades, emphasis has shifted to market approaches, mainly tradable emission permits, i.e., "cap-and-trade" systems.
- However, the piecemeal approach endures with these systems.

- Source-specific, technology-based emission standards initially were dominant regulatory tools.
- In the last two decades, emphasis has shifted to market approaches, mainly tradable emission permits, i.e., "cap-and-trade" systems.
- However, the piecemeal approach endures with these systems.

- Source-specific, technology-based emission standards initially were dominant regulatory tools.
- In the last two decades, emphasis has shifted to market approaches, mainly tradable emission permits, i.e., "cap-and-trade" systems.
- However, the piecemeal approach endures with these systems.

- The federal government is now pressured to add CO_2 to the existing set of criteria air pollutants.
    1. Supreme Court ruled USEPA has the authority to regulate CO_2.
    2. Waxman-Markey H.R. 2454 calls for a tradable permit system with a cap of a 17 percent reduction by 2020 nationwide from 2005 CO_2 emissions.

- The federal government is now pressured to add CO_2 to the existing set of criteria air pollutants.
    1. Supreme Court ruled USEPA has the authority to regulate CO_2.
    2. Waxman-Markey H.R. 2454 calls for a tradable permit system with a cap of a 17 percent reduction by 2020 nationwide from 2005 CO_2 emissions.

- The federal government is now pressured to add CO_2 to the existing set of criteria air pollutants.
  1. Supreme Court ruled USEPA has the authority to regulate CO_2.
  2. Waxman-Markey H.R. 2454 calls for a tradable permit system with a cap of a 17 percent reduction by 2020 nationwide from 2005 CO_2 emissions.

- Several states have implemented $\mathrm{CO_2}$ cap-and-trade for fossil-fueled power plants.
- Again, $\mathrm{CO_2}$ control is treated as separable.
- **However, additional controls on this pollutant may be unwarranted if $\mathrm{CO_2}$, $\mathrm{SO_2}$, and $\mathrm{NO_x}$ control are properly viewed as joint rather than separable.**

- Several states have implemented $\mathrm{CO_2}$ cap-and-trade for fossil-fueled power plants.
- Again, $\mathrm{CO_2}$ control is treated as separable.
- However, additional controls on this pollutant may be unwarranted if $\mathrm{CO_2}$, $\mathrm{SO_2}$, and $\mathrm{NO_x}$ control are properly viewed as joint rather than separable.

- Several states have implemented $\mathrm{CO_2}$ cap-and-trade for fossil-fueled power plants.
- Again, $\mathrm{CO_2}$ control is treated as separable.
- **However, additional controls on this pollutant may be unwarranted if $\mathrm{CO_2}$, $\mathrm{SO_2}$, and $\mathrm{NO_x}$ control are properly viewed as joint rather than separable.**

- Coal switching and flue gas desulphurization (FGD) systems are the principal methods used to reduce $\mathrm{SO_2}$ emissions from coal-fired plants.
- Technologically, most power plant emission control measures affect more than one pollutant (National Research Council, 2004).

- Coal switching and flue gas desulphurization (FGD) systems are the principal methods used to reduce SO_2 emissions from coal-fired plants.
- Technologically, most power plant emission control measures affect more than one pollutant (National Research Council, 2004).

- Example # 1: switching to low-sulfur (which is lower Btu) coal increases particulate, $\mathrm{NO_x}$, and $\mathrm{CO_2}$ 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.
  3. FGD systems generate added $\mathrm{CO_2}$ emissions via the chemical reactions that capture the $\mathrm{SO_2}$.

- Example # 1: switching to low-sulfur (which is lower Btu) coal increases particulate, $\mathrm{NO_x}$, and $\mathrm{CO_2}$ 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.
  3. FGD systems generate added $\mathrm{CO_2}$ emissions via the chemical reactions that capture the $\mathrm{SO_2}$.

- Example # 1: switching to low-sulfur (which is lower Btu) coal increases particulate, $\mathrm{NO_x}$, and $\mathrm{CO_2}$ 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.
  3. FGD systems generate added $\mathrm{CO_2}$ emissions via the chemical reactions that capture the $\mathrm{SO_2}$.

- Example # 1: switching to low-sulfur (which is lower Btu) coal increases particulate, $\mathrm{NO_x}$, and $\mathrm{CO_2}$ 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.
  3. FGD systems generate added $\mathrm{CO_2}$ emissions via the chemical reactions that capture the $\mathrm{SO_2}$.

- Example # 2: Controls aimed specifically at $\mathrm{CO_2}$ also exhibit this jointness.
    1. Amine-based technology is the currently favored technology to capture $\mathrm{CO_2}$ at coal-fired power plants.
    2. Because amine-based sorbents absorb all acid gases, not just $\mathrm{CO_2}$, $\mathrm{SO_2}$ emissions may be well below allowable $\mathrm{SO_2}$ emissions.
    3. This may cause $\mathrm{SO_2}$ marginal control costs to greatly exceed marginal benefits.
    4. Moreover, this technology would consume roughly 25 percent of gross power plant output (Davison, 2007).

- 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).

- Example # 2: Controls aimed specifically at $\mathrm{CO_2}$ also exhibit this jointness.
  1. Amine-based technology is the currently favored technology to capture $\mathrm{CO_2}$ at coal-fired power plants.
  2. Because amine-based sorbents absorb all acid gases, not just $\mathrm{CO_2}$, $\mathrm{SO_2}$ emissions may be well below allowable $\mathrm{SO_2}$ emissions.
  3. This may cause $\mathrm{SO_2}$ marginal control costs to greatly exceed marginal benefits.
  4. Moreover, this technology would consume roughly 25 percent of gross power plant output (Davison, 2007).

- Example # 2: Controls aimed specifically at $\mathrm{CO_2}$ also exhibit this jointness.
  1. Amine-based technology is the currently favored technology to capture $\mathrm{CO_2}$ at coal-fired power plants.
  2. Because amine-based sorbents absorb all acid gases, not just $\mathrm{CO_2}$, $\mathrm{SO_2}$ emissions may be well below allowable $\mathrm{SO_2}$ emissions.
  3. This may cause $\mathrm{SO_2}$ marginal control costs to greatly exceed marginal benefits.
  4. Moreover, this technology would consume roughly 25 percent of gross power plant output (Davison, 2007).

- Example # 2: Controls aimed specifically at $\mathrm{CO_2}$ also exhibit this jointness.
  1. Amine-based technology is the currently favored technology to capture $\mathrm{CO_2}$ at coal-fired power plants.
  2. Because amine-based sorbents absorb all acid gases, not just $\mathrm{CO_2}$, $\mathrm{SO_2}$ emissions may be well below allowable $\mathrm{SO_2}$ emissions.
  3. This may cause $\mathrm{SO_2}$ marginal control costs to greatly exceed marginal benefits.
  4. Moreover, this technology would consume roughly 25 percent of gross power plant output (Davison, 2007).

- Example # 3: Shutting down old, dirty plants to meet the SO_2 cap:
  1. If the shift is to new coal-fired plants, NO_x will also be reduced, since new plants have lower NO_x per Btu.
  2. If the shift is to a new gas-fired plant, NO_x and CO_2 will also be reduced.

- Example # 3: Shutting down old, dirty plants to meet the SO_2 cap:
  1. If the shift is to new coal-fired plants, NO_x will also be reduced, since new plants have lower NO_x per Btu.
  2. If the shift is to a new gas-fired plant, NO_x and CO_2 will also be reduced.

- Example # 3: Shutting down old, dirty plants to meet the $\mathrm{SO_2}$ cap:
    1. If the shift is to new coal-fired plants, $\mathrm{NO_x}$ will also be reduced, since new plants have lower $\mathrm{NO_x}$ per Btu.
    2. If the shift is to a new gas-fired plant, $\mathrm{NO_x}$ and $\mathrm{CO_2}$ will also be reduced.

- 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.

- 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.

- 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.

- 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.

- 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.

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.

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.

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.

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.

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.

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.

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.

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.

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.

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.

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.

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.

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.

- 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,
  2. reduction of good inputs,
  3. reduction of bad outputs,
  4. increase of good outputs.

- 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,
  2. reduction of good inputs,
  3. reduction of bad outputs,
  4. increase of good outputs.

- 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,
  2. reduction of good inputs,
  3. reduction of bad outputs,
  4. increase of good outputs.

- 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,
  2. reduction of good inputs,
  3. reduction of bad outputs,
  4. increase of good outputs.

- 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,
    2. reduction of good inputs,
    3. reduction of bad outputs,
    4. increase of good outputs.

- 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,
  2. reduction of good inputs,
  3. reduction of bad outputs,
  4. increase of good outputs.

- 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,
  2. reduction of good inputs,
  3. reduction of bad outputs,
  4. increase of good outputs.

- 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,
  2. reduction of good inputs,
  3. reduction of bad outputs,
  4. increase of good outputs.

- 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,
    2. reduction of good inputs,
    3. reduction of bad outputs,
    4. increase of good outputs.

- 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,
    2. reduction of good inputs,
    3. reduction of bad outputs,
    4. increase of good outputs.

- Cannot do this with the input or output distance functions.
- Can do this with a directional distance function, which we estimate in this paper.

- Cannot do this with the input or output distance functions.
- Can do this with a directional distance function, which we estimate in this paper.

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

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

- $P(\mathbf{x}, \tilde{\mathbf{x}})$ 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.
- 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.

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

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

- $P(\mathbf{x}, \tilde{\mathbf{x}})$ 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.
- 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.

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

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

- $P(\mathbf{x}, \tilde{\mathbf{x}})$ 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.

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

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

- $P(\mathbf{x}, \tilde{\mathbf{x}})$ 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.
- 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.

- We impose three important properties of the technology directional distance function:
  1. non-negativity,
  2. the translation property (analogous to linear homogeneity of a cost function),
  3. and g-homogeneity (double direction and halve the estimated distance).

- We impose three important properties of the technology directional distance function:
    1. non-negativity,
    2. the translation property (analogous to linear homogeneity of a cost function),
    3. and g-homogeneity (double direction and halve the estimated distance).

- We impose three important properties of the technology directional distance function:
    1. non-negativity,
    2. the translation property (analogous to linear homogeneity of a cost function),
    3. and g-homogeneity (double direction and halve the estimated distance).

- We impose three important properties of the technology directional distance function:
  1. non-negativity,
  2. the translation property (analogous to linear homogeneity of a cost function),
  3. and g-homogeneity (double direction and halve the estimated distance).

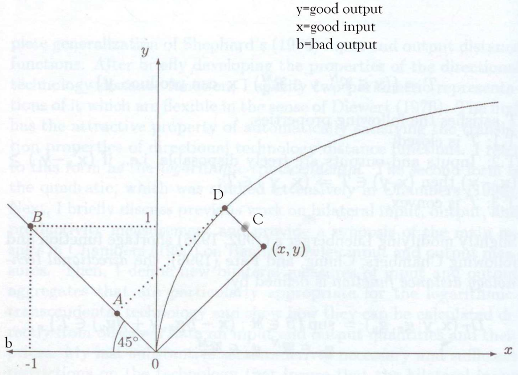

Figure 6.1 The Directional Technology Distance Function

- 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.

- We jointly estimate
  1. a directional technology distance function and
  2. price equations, derived from the shadow profit maximization model, for prodction capital, labor, energy, industrial/commercial, and residential output.

- 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.
- We jointly estimate
  1. a directional technology distance function and
  2. price equations, derived from the shadow profit maximization model, for prodction capital, labor, energy, industrial/commercial, and residential output.

- 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.
- We jointly estimate
  1. a directional technology distance function and
  2. price equations, derived from the shadow profit maximization model, for prodction capital, labor, energy, industrial/commercial, and residential output.

- 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.
- We jointly estimate
  1. a directional technology distance function and
  2. price equations, derived from the shadow profit maximization model, for prodction capital, labor, energy, industrial/commercial, and residential output.

- 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.
- We jointly estimate
  1. a directional technology distance function and
  2. price equations, derived from the shadow profit maximization model, for prodction capital, labor, energy, industrial/commercial, and residential output.

- 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.

- 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.

- 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.

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.
- Details are in Atkinson and Dorfman (2005).
- We allow for heteroskedasticity and autocorrelation of unknown form.

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.
- Details are in Atkinson and Dorfman (2005).
- We allow for heteroskedasticity and autocorrelation of unknown form.

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.
- Details are in Atkinson and Dorfman (2005).
- We allow for heteroskedasticity and autocorrelation of unknown form.

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).
  5. Vintage
  6. Firm Dummies
  7. Time
- All data are standardized so they are unit free.

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).
  5. Vintage
  6. Firm Dummies
  7. Time
- All data are standardized so they are unit free.

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–SO_2, CO_2, and 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).
  5. Vintage
  6. Firm Dummies
  7. Time
- All data are standardized so they are unit free.

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).
  5. Vintage
  6. Firm Dummies
  7. Time
- All data are standardized so they are unit free.

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).
  5. Vintage
  6. Firm Dummies
  7. Time
- All data are standardized so they are unit free.

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).
  5. Vintage
  6. Firm Dummies
  7. Time
- All data are standardized so they are unit free.

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).
  5. Vintage
  6. Firm Dummies
  7. Time
- All data are standardized so they are unit free.

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).
  5. Vintage
  6. Firm Dummies
  7. Time
- All data are standardized so they are unit free.

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).
  5. Vintage
  6. Firm Dummies
  7. Time
- All data are standardized so they are unit free.

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).
  5. Vintage
  6. Firm Dummies
  7. Time
- All data are standardized so they are unit free.

- 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: $g_y = 1; g_{\tilde{\mathbf{y}}} = g_x = g_{\tilde{x}} = -.85$
    3. direction set 3: $g_y = 1; g_{\tilde{\mathbf{y}}} = g_x = g_{\tilde{x}} = -.75$
    4. direction set 4: $g_y = 1; g_{\tilde{\mathbf{y}}} = g_x = g_{\tilde{x}} = -1$

- 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: $g_y = 1; g_{\tilde{\mathbf{y}}} = g_x = g_{\tilde{x}} = -.85$
    3. direction set 3: $g_y = 1; g_{\tilde{\mathbf{y}}} = g_x = g_{\tilde{x}} = -.75$
    4. direction set 4: $g_y = 1; g_{\tilde{\mathbf{y}}} = g_x = g_{\tilde{x}} = -1$

- 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: $g_y = 1; g_{\tilde{\mathbf{y}}} = g_x = g_{\tilde{x}} = -.85$
    3. direction set 3: $g_y = 1; g_{\tilde{\mathbf{y}}} = g_x = g_{\tilde{x}} = -.75$
    4. direction set 4: $g_y = 1; g_{\tilde{\mathbf{y}}} = g_x = g_{\tilde{x}} = -1$

- 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
    2. minor underuse of capital and labor relative to energy.

- 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
    2. minor underuse of capital and labor relative to energy.

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.
- EC remains positive throughout the sample period.

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.
- EC remains positive throughout the sample period.

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.
- EC remains positive throughout the sample period.

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.
- *EC* remains positive throughout the sample period.

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.
- *EC* remains positive throughout the sample period.

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.
- EC remains positive throughout the sample period.

Shadow Prices

- 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.
- The prices of $\mathrm{SO_2}$ are negative as expected for all direction sets.

Shadow Prices

- 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.
- The prices of $\mathrm{SO_2}$ are negative as expected for all direction sets.

Shadow Prices

- 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.
- The prices of $\mathrm{SO_2}$ are negative as expected for all direction sets.

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.

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.

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.

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.

Total Derivatives: Outputs wrt Inputs

- As expected the median total derivative $dSO_2/dS = 1.114$ with a s.d.=.89.
- All good inputs positively affect both types of good outputs.

Total Derivatives: Outputs wrt Inputs

- As expected the median total derivative $dSO_2/dS = 1.114$ with a s.d.=.89.
- All good inputs positively affect both types of good outputs.

Total Derivatives: Outputs wrt Inputs

- As expected the median total derivative $dSO_2/dS = 1.114$ with a s.d.=.89.
- All good inputs positively affect both types of good outputs.

Total Derivatives: Inputs wrt Inputs

- Pollution control capital is a substitute for all good inputs.
- More sulfur increases the amounts of all inputs, including pollution control capital.

Total Derivatives: Inputs wrt Inputs

- Pollution control capital is a substitute for all good inputs.
- More sulfur increases the amounts of all inputs, including pollution control capital.

Total Derivatives: Inputs wrt Inputs

- Pollution control capital is a substitute for all good inputs.
- More sulfur increases the amounts of all inputs, including pollution control capital.

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.
- Isolated Control strategies have been developed for SO_2 and NO_x.
- The proposed CO_2 control strategy has also been developed in isolation from the other two pollutant control strategies.

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.
- Isolated Control strategies have been developed for SO_2 and NO_x.
- The proposed CO_2 control strategy has also been developed in isolation from the other two pollutant control strategies.

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.
- Isolated Control strategies have been developed for SO_2 and NO_x.
- The proposed CO_2 control strategy has also been developed in isolation from the other two pollutant control strategies.

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.
- Isolated Control strategies have been developed for SO_2 and NO_x.
- The proposed CO_2 control strategy has also been developed in isolation from the other two pollutant control strategies.

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.
- Isolated Control strategies have been developed for SO_2 and NO_x.
- The proposed CO_2 control strategy has also been developed in isolation from the other two pollutant control strategies.

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.
- Isolated Control strategies have been developed for SO_2 and NO_x.
- The proposed CO_2 control strategy has also been developed in isolation from the other two pollutant control strategies.

- Control strategies cannot be least-cost when policy makers ignore the substantial interdependence that we have observed.
- Both NO_x and SO_2 will be over-controlled if an independent CO_2 cap-and-trade strategy is adopted.

- **Control strategies cannot be least-cost when policy makers ignore the substantial interdependence that we have observed.**
- **Both NO_x and SO_2 will be over-controlled if an independent CO_2 cap-and-trade strategy is adopted.**

- **Control strategies cannot be least-cost when policy makers ignore the substantial interdependence that we have observed.**
- **Both NO_x and SO_2 will be over-controlled if an independent CO_2 cap-and-trade strategy is adopted.**

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)

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

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