A Causal Inference Framework to Support Policy Decisions by Evaluating the Effectiveness of Past Air Pollution Control Strategies for the Entire United States

Project 4 of the Harvard/MIT ACE Center

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Methodological Overview

Novel Use of Statistics and Observed Data Along the Accountability Chain
Accountability Studies of Power Plant Policies and Interventions

Which air pollution control strategies targeting electric power generating facilities have been most effective in reducing emissions, air pollution, and preventing adverse health outcomes?

**Objective 1:**
Develop an open access and reproducible linked data base and statistical software for causal inference and mediation analysis to evaluate causal effects of any regulatory action.

**Interventions (A) on Power Plants**
- Allowances/Compliance
- Fuel types/content
- Scrubber technology

**Objective 2:**
Causal Effects of A on Emissions (2a), Air Quality (2b)
- Propensity score models
- Comparison of regulatory strategies

**Objective 3:**
Causal Effects of A on Health
- Susceptibility/vulnerability
- New methods for interference

**Objective 4:**
Mediation Analysis
- Estimate the the direct and indirect effects of past control strategies implemented at power generating facilities on ambient quality and health
- Cobenefits

**Emissions**
- $SO_2$, $NO_x$, $CO_2$, $PM_{2.5}$

**Air Quality**
- $PM_{2.5}$, $O_3$

**Morbidity & Mortality**
Traditional Role of Statistics/Epidemiology/Observations

The “bottom of the chain”

“Health Effects” of pollution exposure

Using observed AQ/health data

Air Quality
PM$_{2.5}$, O$_3$

Statistical Methods/Observed Data

Morbidity & Mortality
But What About “Health Effects” of Policies? or interventions or emissions?
But What About “Health Effects” of Policies? or interventions or emissions?

Traditional Approach

Step (1): Predict impact on AQ with models

Step (2): Apply epi estimates to modeled AQ changes

\[ (1) + (2) \Rightarrow \text{(indirectly) inferred health benefit of a policy/intervention} \]
Methods Spanning the Whole Chain
to evaluate interventions on (emissions from) power plants

1. Observed data on all links in the chain
   - Air markets data/CEMs, AQS/data-fused predictions, Medicare health outcomes

2. Rigorous statistical methods
   - Focus on causal inference methodology

3. “Reduced complexity” AQ models
Acknowledging Pollution Transport

**Key challenge:** Transport $\Rightarrow$ health at a given location affected by interventions at *many* sources
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Two areas of methods development:

1. "Reduced Complexity Models" to obtain source-receptor matrices
   - Maintain *computational scalability* and *individual source impacts*

2. Statistical Methods for Causal inference
   - Focus on methods for *interference*
   - New horizon for causal inference research

Deploy new methods epidemiological/health effects studies focusing on power plants
Reduced Complexity Models for Individual Source Impacts

Source-Receptor Mapping
Which Populations Are Subject to Which Interventions?

Source ↔ Population link for 1Ks of point sources and 10Ks of population locations

Interventions/Emissions from Power Plants

Affect

Pollution/Health at Population Locations (ZIP Codes)
“Reduced Complexity” Models: desirable qualities

1. Individual source impacts

2. Broad spatial coverage (e.g., entire US)

3. Fine spatial resolution (e.g., ZIP code, ~1 km)

4. Flexibility to apply to different periods, time spans, and interventions
“Reduced Complexity” Methods Development

1. HYSPLIT dispersion approach (HyADS)
   - Repurposing (+ modernizing) of established tool

2. Intervention Model for Air Pollution (InMAP)
   - Developed by CMU/UW ACE Center
   - + added “front-end” to retrieve some capabilities with R software

3. “Fully statistical” approach using emissions/AQ time series
   - At earlier stages, but showing promise
   - Using methods developed from ACE Project 2
   - (Poster by Kevin Cummiskey)
HYSPLIT Average Dispersion (HyADS)

Use HYSPLIT to model dispersion of emissions → populations

- Simulate dispersion of 100 parcels starting at individual stack
- Parcels tracked for 10 days and locations aggregated to ZIP codes
- Repeat at 6 hour intervals daily
- Weight by monthly emissions

Notes: omit near-source impacts, parcels not resuspended, only count beneath planetary boundary layer
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ZIP code coal emissions exposure from all coal power plants using HyADS
Comparison of Metrics for Coal Power Plant Exposure – 2005

Hybrid CMAQ-DDM / Observation Impacts

Ivey et al. 2015 Geos. Mod. Dev.

HyADS Impacts

InMAP Impacts
Quantitative Comparisons of Exposure Metrics

<table>
<thead>
<tr>
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<th>All Regions</th>
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<tbody>
<tr>
<td>Obs $SO_4^{2-}$</td>
<td>385</td>
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<tr>
<td>Obs PM$_{2.5}$</td>
<td>1050</td>
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<td>21007</td>
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<td>Spearman</td>
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Color scale:
- Dark blue: 0.5
- Light blue: 0.6
- Light purple: 0.7
- Light yellow: 0.8
- Orange: 0.9
- Dark yellow: 1.0
## Quantitative Comparisons of Exposure Metrics

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- Pearson and Spearman correlation coefficients are indicated by the color scale range from 0.5 to 1.0.
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Legend:
- Pearson
- Spearman
Quantitative Comparisons of Exposure Metrics

Hybrid – DDM

InMAP

HyADDS

InMAP
Example application - ranking individual facilities by their impacts

1. Rank sources by population-weighted impact (top 6 facilities shown)
2. Highlight ZIP codes in which these facilities contribute the maximum population-weighted exposure
Key Features of the HyADS Approach

Exchange *complexity* for *computational scalability* → flexibility:

- **Very** simplified chemistry/transport
- **Very** flexible sets of sources—source-specific impacts
- **Very** flexible time frames
  - Daily, Monthly, Seasonal, Annual impacts
  - No fixing meteorology or other conditions at a “base year”
- **Very** computationally scalable
  - 100K’s of trajectories in ∼ hours
  - Open access tools for parallel computation (poster by Christine Choirat)
Reduced Complexity Models for Individual Source Impacts

Epidemiological Analysis
**Health improvements in the US associated with reduced coal emissions between 2005 and 2012**

**Question:** Did ZIP codes with larger decreases in (coal emissions) exposure exhibit larger health improvements?

Decrease in HyADS exposure, 2005 - 2012
Health improvements in the US associated with reduced coal emissions between 2005 and 2012

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Health improvements in the US associated with reduced coal emissions between 2005 and 2012

**Question:** Did ZIP codes with larger decreases in (coal emissions) exposure exhibit larger health improvements?

- Associate “exposure” change with changing Medicare health outcomes rates
A Source-Oriented Approach to Coal Power Plant Health Effects

**Question:** Do ZIP codes with higher exposure to coal power plants have higher rates of IHD hospitalizations? (poster by Kevin Cummiskey)

Propensity score analysis of ZIP codes **High vs. Low** exposed to coal power plant emissions (measured with InMAP) on Medicare IHD

Estimated IRRs associated with IHD hospitalizations

<table>
<thead>
<tr>
<th>Region</th>
<th>Industrial Midwest</th>
<th>Northeast</th>
<th>Southeast</th>
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<tr>
<td>IRR</td>
<td>1.02</td>
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<td>1.06</td>
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<td>CI</td>
<td>(1.00, 1.04)</td>
<td>(1.06, 1.09)</td>
<td>(1.04, 1.08)</td>
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Statistical Methods Development

Causal Inference Methodology
“Health Effects” of Pollution $\rightarrow$ “Health Effects” of Policies

Person’s exposure is self evident in a traditional epi study

- Health outcome measured on individual
- Exposure measured at individual’s residence
“Health Effects” of Pollution $\rightarrow$ “Health Effects” of Policies

Person’s exposure is self evident in a traditional epi study
  - Health outcome measured on individual
  - Exposure measured at individual’s residence

“Exposure” to a policy is more complex
  - Person is “exposed” to *multiple* interventions at *many* sources
    - Virtually all statistical methods assume this *doesn’t* occur
    - Causal inference on a “network” of sources and populations

⇒ Requires new methodology for *causal inference with interference*
Interconnected Causal Questions with Interference
More complicated than in traditional epi study

Question: How does installing a scrubber on a power plant affect health?
Answer: It depends on which power plant and which location.
Interconnected Causal Questions with Interference
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Question: How does installing a scrubber on a power plant affect health?
Answer: It depends on which power plant and which location.

Question: What is the average effect of installing a scrubber on the closest power plant?
Answer: It depends on how many scrubbers are on the other “upwind” power plants.
Interconnected Causal Questions with Interference
More complicated than in traditional epi study

Question: How does installing a scrubber on a power plant affect health?
Answer: It depends on which power plant and which location.

Question: What is the average effect of installing a scrubber on the closest power plant?
Answer: It depends on how many scrubbers are on the other “upwind” power plants.

Question: What is the average effect of installing a scrubber on “upwind” power plants?
Answer: It depends whether the closest power plant has a scrubber.
Causal Inference With Interfering Units for Cluster and Population Level Treatment Allocation Programs

Poster by Georgia Papadogeorgou

Estimating Effectiveness of Power Plant Emissions Controls for Reducing Ambient Ozone Pollution

- **Intervention:** SCR to reduce NO\textsubscript{x} emissions
- Installed (or not) on 152 (321) coal or gas plants in 2004
- **Outcome:** O\textsubscript{3} measured at 921 monitors
New estimators for “Direct” and “Indirect” Effects

“Direct effect” of installing SCR for a fixed policy on “upwind” plants

```
<table>
<thead>
<tr>
<th>α</th>
<th>DE(α)</th>
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<tbody>
<tr>
<td>0.1</td>
<td>0.00</td>
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<tr>
<td>0.2</td>
<td>-0.01</td>
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<tr>
<td>0.3</td>
<td>-0.02</td>
</tr>
<tr>
<td>0.4</td>
<td>-0.03</td>
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SCR → local $O_3$ with, waning effectiveness with more SCRs on “upwind” plants

“Indirect effect” of installing SCR on “upwind” plants

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<table>
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<th>IE(0.1, α)</th>
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<tr>
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More SCR on “upwind” plants → less local $O_3$
Bipartite Causal Inference with Interference

Extending to “direct” effect of SCR on nearby Medicare CVD vs. “indirect” effect of SCR at “upwind” plants

SCR nearby and “upwind” reduces CVD hospitalizations
Other Ongoing Statistical Methods Development
In addition to methods for interference

Causal inference to confront the realities of air pollution work:

- Bayesian nonparametric causal mediation analysis (Poster by Chanmin Kim)
- Statistical network analysis (Poster by Kevin Cummiskey)
- Sensitivity to PM modeling choices (Poster by Xiao Wu)
- Generalized propensity score matching for continuous pollution exposure (Poster by Xiao Wu)
- Causal exposure-response estimation
- Spatial confounding adjustment
- Causal inference for mismeasured exposure
- Effectiveness subgroup identification
- Strong confounding/limited propensity score overlap
Summary and Future Directions

- Continue to refine/validate HyADS approach and other reduced-complexity models
  - In collaboration with CMU/UW ACE Center
- Deploy reduced-complexity models in epi studies using observed health outcomes
- Causal inference statistical methodology
  - Focus on causal inference with interference
  - New horizon for statistical methodology
  - Necessary to confront statistical challenges of evaluating pollution policies
- Extend to studies of different policies and interventions on power plants