Bipartite interference: Estimating health effects of power plant interventions

Fabrizia Mealli

European University Institute
fabrizia.mealli@eui.eu

with Cory Zigler (UT Austin) and Laura Forastiere (Yale)

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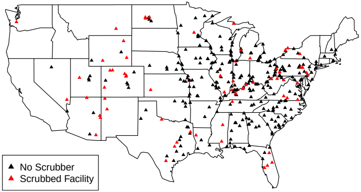
Major Pollution Source: Power Plants

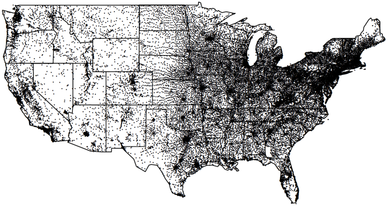
⇒ Many regulations to reduce emissions

Interventions at Power Plants:
"Scrubber" Installation
⇝ Reduce SO_2 emissions



Affect?
⟶

Health at Population Locations
(Zip Codes)



Question: Do scrubbers on coal-fired power plants causally affect hospitalizations for Ischemic Heart Disease (IHD) among Medicare beneficiaries?

Formalization of Bipartite Structure

Two types of observational units:

1. *Intervention Units*
   - $\mathcal{P} = \{p_1, p_2, \ldots, p_j, \ldots, p_J\}$: a set of J power plants, where interventions occur (or not)
   - $S_j = 1/0$ denotes presence/absence of intervention
   - Treatment allocation: $\mathbf{S} = (S_1, \ldots, S_j, \ldots, S_J)$
   - Space of possible vectors of treatment allocations: $\mathcal{S}(J)$
   - Covariates $\mathbf{X}^{int} = (\mathbf{X}_1^{int}, \ldots, \mathbf{X}_j^{int}, \ldots, \mathbf{X}_J^{int})$
2. *Outcome Units*
   - $\mathcal{M} = \{m_1, m_2, \ldots, m_i, \ldots, m_n\}$: a set of n locations, where outcomes are measured
   - Y_i denotes the outcome of interest
   - Covariates: $\mathbf{X}^{out} = (\mathbf{X}_1^{out}, \ldots, \mathbf{X}_i^{out}, \ldots, \mathbf{X}_n^{out})$

Potential Outcomes

- $Y_i(\mathbf{s})$ potential outcome that would be observed at outcome unit i under treatment allocation $\mathbf{s}$, $\mathbf{s} \in \mathcal{S}(J)$
- No multiple versions of treatment: $Y_i(\mathbf{s}) = Y_i(\mathbf{s}')$ $\forall i$ when $\mathbf{s} = \mathbf{s}'$

(*Zigler and Papadogeorgou, 2021; Papadogeorgou, Mealli, Zigler, 2019*)

Examples and Challenges

Examples:

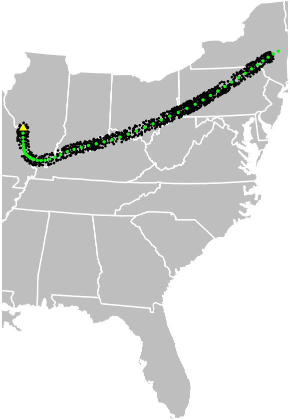
1. *Economics of housing (Stock, 1989)*
    - Intervention units: Hazardous-waste disposal sites where treatments (cleaning up) can be applied
    - Outcome units: Locations where outcomes (e.g., housing values) are measured
2. *Education economics (Crema, 2022)*
    - Intervention units: Neighborhoods which may be exposed to openings of charter schools (treatment)
    - Outcome units: Traditional public schools (TPS) where outcome (e.g., racial segregation) are measured

Non trivial differences in:

- the formulation of the estimands
- the assignment mechanism
- different types and sources of confounding

Interference Mapping and Causal Quantities

Using Long-range Pollution Transport Models (HyADS)
Henneman et al (2019)



- Emissions originating at a power plant (**yellow triangle**) *move*

  ⇝ Long distances towards conversion to harmful pollution

- Potential outcomes for zip code i:

  ⇝ Y_i(power plants that pollute over i)

- Estimands that compare the potential outcomes

  ⇝ if the *most influential (or closest)* power plant were treated

  ⇝ if the 10 most influential power plants were treated

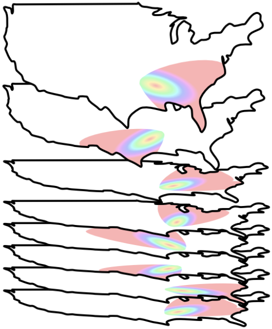
  ⇝ any other intervention allocation

Interference Mapping and Causal Quantities

Using Long-range Pollution Transport Models (HyADS)

Henneman et al (2019)

Use atmospheric transport models to simulate emissions events starting at individual stack



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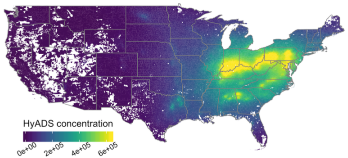
Interference Mapping

"Source-Receptor Matrix" or "Bipartite Weighted Directed Network"

- $t_{ij} \equiv$ influence of j^{th} power plant on i^{th} location
  - i.e., # of times dispersed parcels from p_j pass over location m_i (re-scaled to a max of 1)
  - directly output by HyADS atmospheric model



- Interference mapping: $n \times J$ matrix, T:

$$
\begin{array}{c} \\ ZIP_1 \\ \vdots \\ ZIP_i \\ \vdots \\ ZIP_n \end{array}
\begin{array}{c} \begin{array}{ccccc} PP_1 & \dots & PP_j & \dots & PP_J \end{array} \\
\begin{pmatrix}
t_{11} & \dots & t_{1j} & \dots & t_{1J} \\
\vdots & \dots & \vdots & \dots & \vdots \\
t_{i1} & \dots & t_{ij} = (\text{influence of } PP_j \to ZIP_i) & \dots & t_{iJ} \\
\vdots & \dots & \vdots & \dots & \vdots \\
t_{n1} & \dots & t_{nj} & \dots & t_{nJ}
\end{pmatrix} \end{array}
$$

Bivariate Treatment

1. Outcome unit i 's "key associated" intervention unit: $j^*_{(i)}$, i.e., the power plant that is most influential for ZIP code i
   - $j^*_{(i)} \equiv j : t_{ij} = \max_j \{t_{i1}, \ldots, t_{ij}, \ldots t_{iJ}\}$

2. "Individual" Treatment: $Z_i = S_{j^*_{(i)}}$, i.e., scrubber status of the *key associated* power plant $j^*_{(i)}$
   - $Z_i = 0, 1$ according to whether the key power plant has a scrubber or not

3. "Upwind" Treatment: Function of the scrubber statuses of all other "linked" power plants
   - "Exposure Mapping:" $g_i(\cdot; T) : \{0, 1\}^{J-1} \rightarrow \mathcal{G}_i$
   - $g_i(\mathbf{S}, T) = G_i = \sum_{j \neq j^*_{(i)}} t_{ij} S_j$
   - HyADS-weighted upwind treatment rate

(*Aronow, Samii, 2017; Forastiere et al., 2021*)

"Upwind Interference" Assumption

(Adaptation of SUTVA)

$$Y_i(\mathbf{S}) = Y_i(Z_i, G_i) = Y_i(Z_i', G_i') = Y_i(\mathbf{S}')$$

- Reduces interference to depend only on Z_i and G_i (not on the entire $\mathbf{S}$)
- Hospitalizations are the same under different $\mathbf{S}$ if the treatment of the key power plant and the "upwind" treatment rate are the same
- **The key assumption** about interference

Assignment mechanism governing the joint treatment:

$$P\left(\mathbf{Z}, \mathbf{G} \mid \mathbf{X}^{out}, \mathbf{X}^{int}, \{Y_i(z, g), z \in \{0, 1\}, g \in \mathcal{G}\}\right)$$

“Direct” Effects in the Bipartite Setting

Average dose-response under key-associated treatment z and upwind treatment g

$$\mu(z,g) = \mathbb{E}_{X^{int},X^{out}}\left[\mathbb{E}_{Y(\cdot)|X^{int},X^{out}}\left[Y_i(z,g) \mid X_i^{int}, X_i^{out}\right]\right]$$

The “direct” effect of treating the key plant while holding fixed the “upwind” treatments:

$$\tau(g) = \mu(1,g) - \mu(0,g)$$

“Overall” average over the distribution of “upwind” treatments:

$$\tau = \sum_{g \in \mathcal{G}} \tau(g) P(G_i = g)$$

“The effect on IHD hospitalizations that we are expecting to have in a zipcode from installing a scrubber on the *key associated* power plant”

"Indirect" or "Spillover" Effects in the Bipartite Setting

The "indirect" or "upwind" effect of installing scrubbers on upwind power plants without changing the key plant:

$$\delta(g; z) = \mu(z, g) - \mu(z, g^{min})$$

"Overall" average over the distribution of "upwind" treatments:

$$\Delta(z) = \sum_{g \in \mathcal{G}} \delta(g; z) P(G_i = g)$$

"The effect on IHD hospitalizations that we are expecting to have in a zipcode from installing more scrubbers on upwind plants"

Confounding Specification

Ignorability of the Joint Treatment:

$$Y_i(z, g) \perp\!\!\!\perp Z_i, G_i \mid \{\mathbf{X}_j^{int}\}_{j:t_{ij}>0}, \mathbf{X}_i^{out}, \qquad \forall z \in \{0, 1\}, g \in \mathcal{G}_i, \forall i$$

$\mathbf{X}_i^{out}$ includes: population, urbanicity, race/ethnicity, education, HH income, poverty, occupied housing, migration, smoking, region, temperature, humidity, Medicare age, sex.

$$\{\mathbf{X}_j^{int}\}_{j:t_{ij}>0} = \left\{\mathbf{X}_{j^*_{(i)}}^{int}, \{\mathbf{X}_j^{int}\}_{j \neq j^*_{(i)}:t_{ij}>0}\right\}$$

$\mathbf{X}_{j^*_{(i)}}^{int}$ includes: operating time, heat input, %operating capacity, ARP phase II participation, NO_x controls sulfur content of coal *of power plant* $j^*_{(i)}$

$\{\mathbf{X}_j^{int}\}_{j \neq j^*_{(i)}:t_{ij}>0}$ includes: "upwind" versions of power plant characteristics (e.g., the HyADS-weighted operating time of upwind plants)

Individual and Neighborhood Propensity Scores

Extension of Forastiere et al. (2021)

View "individual" and "upwind" treatments as bivariate treatment and estimate a **joint propensity score**:

$$\psi_i(z, g; x^{int}, x^{out}) = P\left(Z_i = z, G_i = g \mid \{\mathbf{X}_j^{int}\}_{j:t_{ij}>0} = x^{int}, \mathbf{X}_i^{out} = x^{out}\right)$$

Further decompose into:

$$\begin{aligned}
&\psi_i(z, g; x^{int}, x^{out}) \\
= \quad & P\left(Z_i = z \mid \{\mathbf{X}_j^{int,z}\}_{j:t_{ij}>0} = x^{int,z}, \mathbf{X}_i^{out,z} = x^{out,z}\right) \qquad (1) \\
& \times P\left(G_i = g \mid Z_i = z, \{\mathbf{X}_j^{int,g}\}_{j:t_{ij}>0} = x^{int,g}, \mathbf{X}_i^{out,g} = x^{out,g}\right) \qquad (2)
\end{aligned}$$

$(1) \equiv \phi_i(z; x^{int,z}, x^{out,z}) \equiv$ "individual propensity sore"

$(2) \equiv \lambda_i(g; z, x^{int,g}, x^{out,g}) \equiv$ "upwind propensity score"

Estimation strategy

Extension of Forastiere et al. (2021)

1. Estimate ϕ_i and λ_i: $\hat{\phi}_i$, $\hat{\lambda}_i$
2. Stratify zip codes into $K = 5$ strata based on based on $\hat{\phi}_i$
3. Specify and estimate $Y_i(z, g)|\hat{\lambda}_i \sim f^y(z, g, \hat{\lambda}; \theta_k)$; derive predicted values $\hat{Y}_i(z, g)$
4. Estimate within-stratum dose-response function $\mu_k(z, g)$:

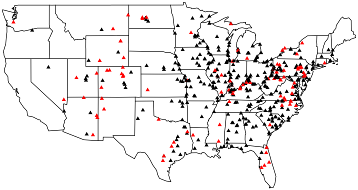
$$\widehat{\mu}_k(z, g) = \frac{\sum_{i \in n_k} \widehat{Y}_i(z, g)}{n^k}$$

5. Obtain an overall estimate: $\widehat{\mu}(z, g) = \sum_{k=1}^{K} \widehat{\mu}_k(z, g)\pi^k$
6. Calculate Direct and Upwind effects
7. Intervention-Unit Bootstrap - not exactly right, but shown via simulations to be conservative as a measure of model and design variability

Power Plant and Zip Code Data

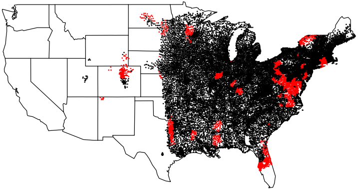
Integrated with HyADS atmospheric model

472 Coal-fired power plants operating in 2005



Affect →

Medicare IHD Hospitalizations in 2005 at 25,553 zip codes (overlap criteria)

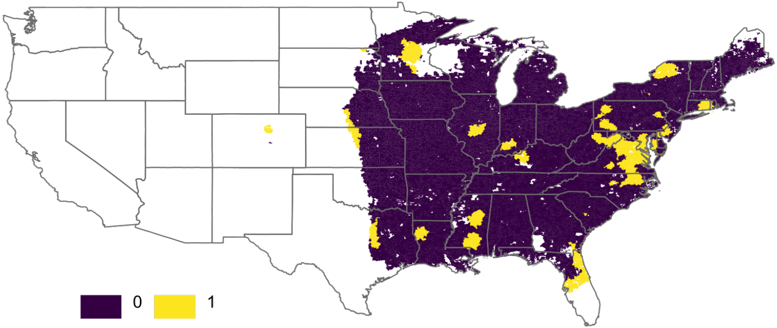


- 106 with scrubbers installed
- Information on emissions, plant size, operating capacity, other controls, etc. (EPA)

- Information on population demographics (Census, Medicare), weather (NOAA), smoking rates (CDC)

Individual Treatment

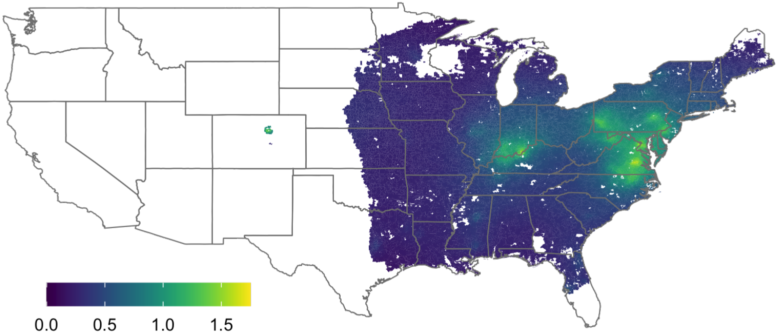
Whether the **most influential** plant has a scrubber



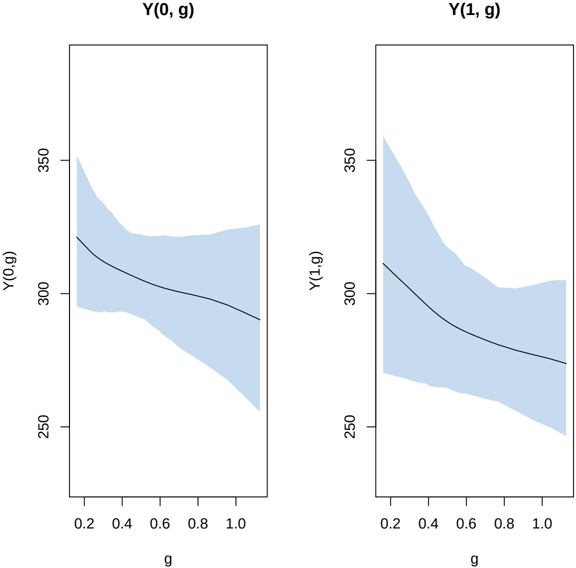
$Z_i = 0$ if j^* has no scrubber
$Z_i = 1$ if j^* has scrubber (2,753 zip codes)
278 power plants are key-associated and 35 have scrubber

"Upwind" Treatment

HyADS-weighted treatment rate of upwind plants



Average Dose-Response for $Y(z, g)$



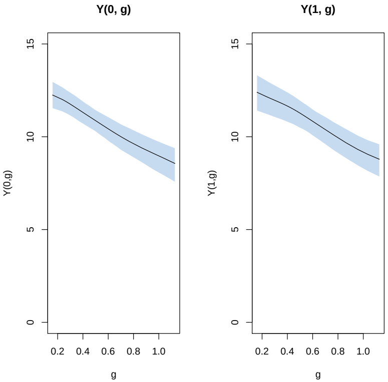
Estimated Effects of Scrubbers on IHD Hospitalization

- Average “direct” effect of installing a scrubber on the key power plant (τ)
  - **Most influential plant**: -23 (-38, 14)

  ... hospitalizations per 10K person-years

- Average “upwind” effect of installing more scrubbers on “upwind” plants ($\Delta(z)$):
  - **Most influential** plant:
    - If $z = 1$: -18 (-39, 2)
    - If $z = 0$: -14 (-37, 2)

Average Dose-Response for $PM_{2.5}(z, g)$



$\hat{\tau}$=-0.37 (-0.32, 0.84);

$\Delta(0)$=-1.34 (-1.75, -0.99); $\Delta(1)$=-1.16 (-1.63, -0.80)

Summary

- Causal inference in bipartite observational settings
  - ▷ Introduce new types of causal questions and estimands
  - ▷ Complex exposure patterns generate different types of interference, going beyond unit-to-unit or spatial interference
  - ▷ New notions of confounding and homophily
  - ▷ New methods for **bipartite causal inference**
- Relevance for many other interventions with a clear distinction between intervention and outcome units

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