

Adjusting for Unmeasured Spatial Confounding with Distance Adjusted Propensity Scores

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Air Quality Regulations

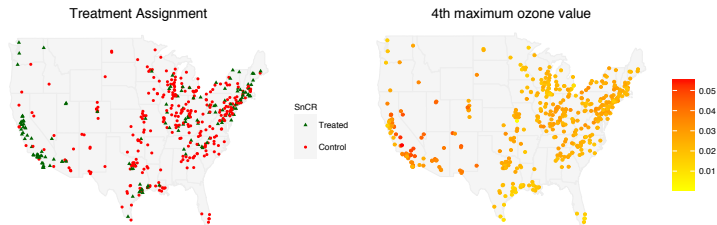
- Regulations
 - Clean Air Interstate Rule (CAIR)
 - Cross-State Air Pollution Rule (CSAPR)
 - 1990 Clear Air Act
 - Acid Rain Program
- Power plants followed various compliance strategies
- Comparative effectiveness of NO_x emission control technologies on ambient ozone levels

Motivation

- Ozone is a secondary pollutant (Allen, 2002)
 - Created from chemical reactions in the atmosphere
 - Sunlight, Higher temperature
- Selective Catalytic Reduction (SCR) and Selective Non-Catalytic Reduction (SNCR) are the most effective in reducing NO_x
- Reductions in NO_x emissions \rightarrow reduction in ozone concentrations
- Effect of SCR/SNCR on ambient ozone

Data

- Coal and natural gas power plants during June-August 2004
- $A = 1$ if at least half of facility heat input is used by units with installed SCR/SNCR technologies, $A = 0$ otherwise
- 152 treated facilities, 321 controls
- Y : NO_x emissions / 4th maximum ambient ozone concentration



Notation

- For unit i
 - Treatment $A_i \in \{0, 1\}$
 - Potential outcomes $Y_i(1), Y_i(0)$ (SUTVA)
 - Covariates $C_i = (C_{i1}, C_{i2}, \dots, C_{ip})$

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- Propensity score matching
 - PS model $P(A = 1|\mathbf{C})$
 - Match treated units to controls with similar PS estimates

Unmeasured spatial confounding

- Confounders $\mathbf{C} = (\mathbf{X}, \mathbf{U})$
 - \mathbf{X} are observed, \mathbf{U} are unobserved
- If \mathbf{U} varies spatially, can we adjust for it?

Unmeasured spatial confounding

- Confounders $\mathbf{C} = (\mathbf{X}, \mathbf{U})$
 - \mathbf{X} are observed, \mathbf{U} are unobserved
- If \mathbf{U} varies spatially, can we adjust for it?
- Temperature, and weather conditions may confound the relationship of NO_x control strategies and ambient ozone.
 - Temperature, barometric pressure, humidity
- Weather and atmospheric covariate information varies spatially

Unmeasured Spatial Confounding

- Observed variables \mathbf{X} :
 - Use the propensity score to adjust for the observed confounders
 - $P(A_i = 1|X_i) = f(X_i) = \text{expit}(X_i^T \beta)$
- Unmeasured spatial confounders \mathbf{U}
 - The correlation of \mathbf{U} is high for small enough distances
 - If a matched pair is sufficiently close, the treated and control units will have similar values of \mathbf{U}

Distance Adjusted Propensity Score Matching

- For a treated unit i and a control unit j define

$$DAPPS_{ij} = w|PS_i - PS_j| + (1 - w) * Dist_{ij}, \quad w \in [0, 1]$$

where PS propensity score estimates, and $Dist$ spatial proximity.

- w expresses our belief of the relative importance of the observed and unobserved confounders
- $Dist$ is the measure that expresses our belief of similarity of U as a function of distance

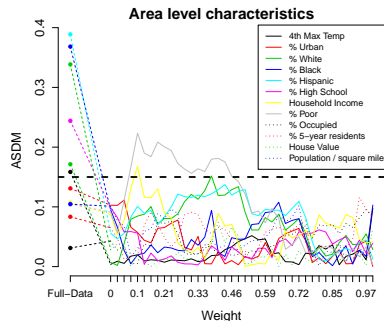
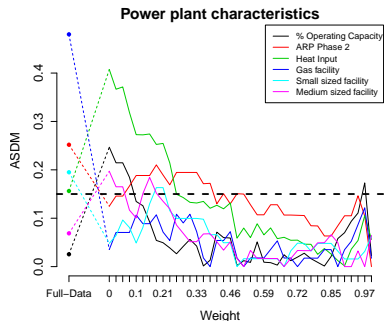
Choosing w

$$DAPS_{ij} = w|PS_i - PS_j| + (1 - w) * Dist_{ij}, w \in [0, 1]$$

- Interplay between distance of observed covariates and distance of matched pairs
- w can be specified using subject-matter knowledge on an unmeasured spatial confounder
- Automated procedure
 - Re-calculates DAPS and performs matching for many values of w
 - Balance of the observed covariates is assessed
 - The smallest value that achieves covariate balance is chosen

Checking covariate balance

- Absolute standardized difference of means as a function of w



Matches

Naive pairs



DAPSm pairs

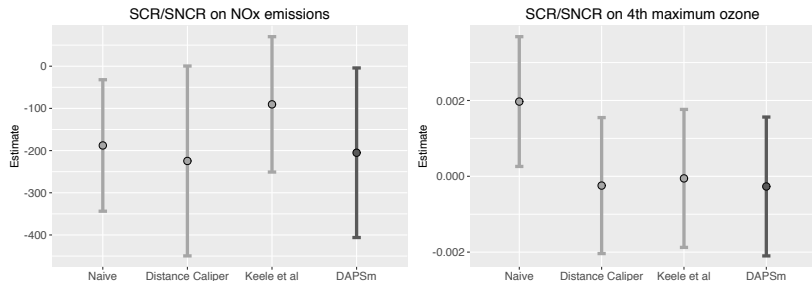


- Average distance of matched pairs

- Naïve: 1066 miles

- DAPSm: 141 miles

Results



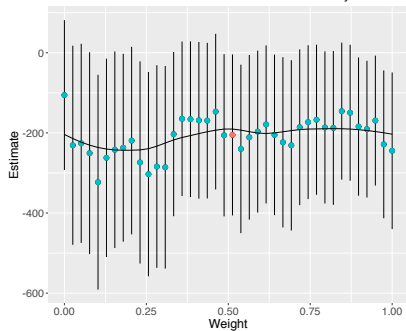
- 205 NO_x tons (95% CI: 4 – 406)
- -0.27 parts per billion (95% CI: -2.1 – 1.56)

The national ozone air quality standard of 70 parts per billion.

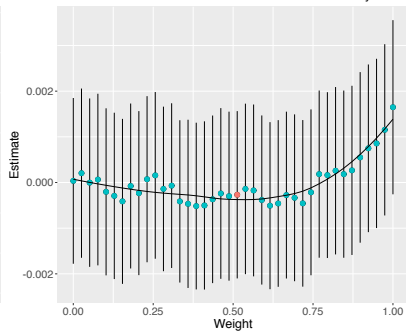
Keele et al. (2015)

DAPSm results as a function of w

Estimates with 95% confidence intervals for NOx analysis



Estimates with 95% confidence intervals for Ozone analysis



Conclusions

- SCR/SNCR control technologies seem to be associated with reduced NO_x emissions
- Their effect on ozone is not significant
- Unobserved confounding can lead to severe bias of estimates

References

- Allen, J. (2002). Chemistry in the Sunlight. *Earth Observatory NASA* .
- Keele, L., Titiunik, R., and Zubizarreta, J. (2015). Enhancing a Geographic Regression Discontinuity Design Through Matching to Estimate the Effect of Ballot Initiatives on Voter Turnout. *Journal of Royal Statistical Society A* **178**, 223–239.
- Rosenbaum, P. R. and Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika* **70**, 41–55.