Causal Estimates of the Relationship between Fine Particulate Matter and Mortality using Attainment Status under the Clean Air Act Amendments

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Introduction

- Estimating causal effects of pollution on health essential for informing policy
  - Efficient policy balances costs and benefits
  - Most benefit estimates based on correlational analysis
- Pollution exposure likely endogenous
  - Air quality “amenity value” capitalized into housing prices
    - Wealthier/sicker people live in cleaner areas
    - Unobserved investments of wealthy/sick
  - Cities attract high-skilled workers
    - Source of emissions
    - Source of lots of amenities: health care, stress, arts, etc.

→ Omitted variable and simultaneity bias

TABLE 2

CROSS-SECTIONAL AND FIXED EFFECT REGRESSION ESTIMATES OF THE RELATIONSHIP BETWEEN POLLUTION AND HEALTH, BRFSS 2001–06

	Cross-sectional model		
	1	2	3
1. Any teeth missing (mean = 0.480, SD = 0.500)			
AQI*10	0.063*	0.058*	0.059*
	[0.033]	[0.031]	[0.031]
Observations	312,963	312,963	312,963
R^2	0.247	0.262	0.265
Behavior	N	Y	Y
Other health	N	N	Y

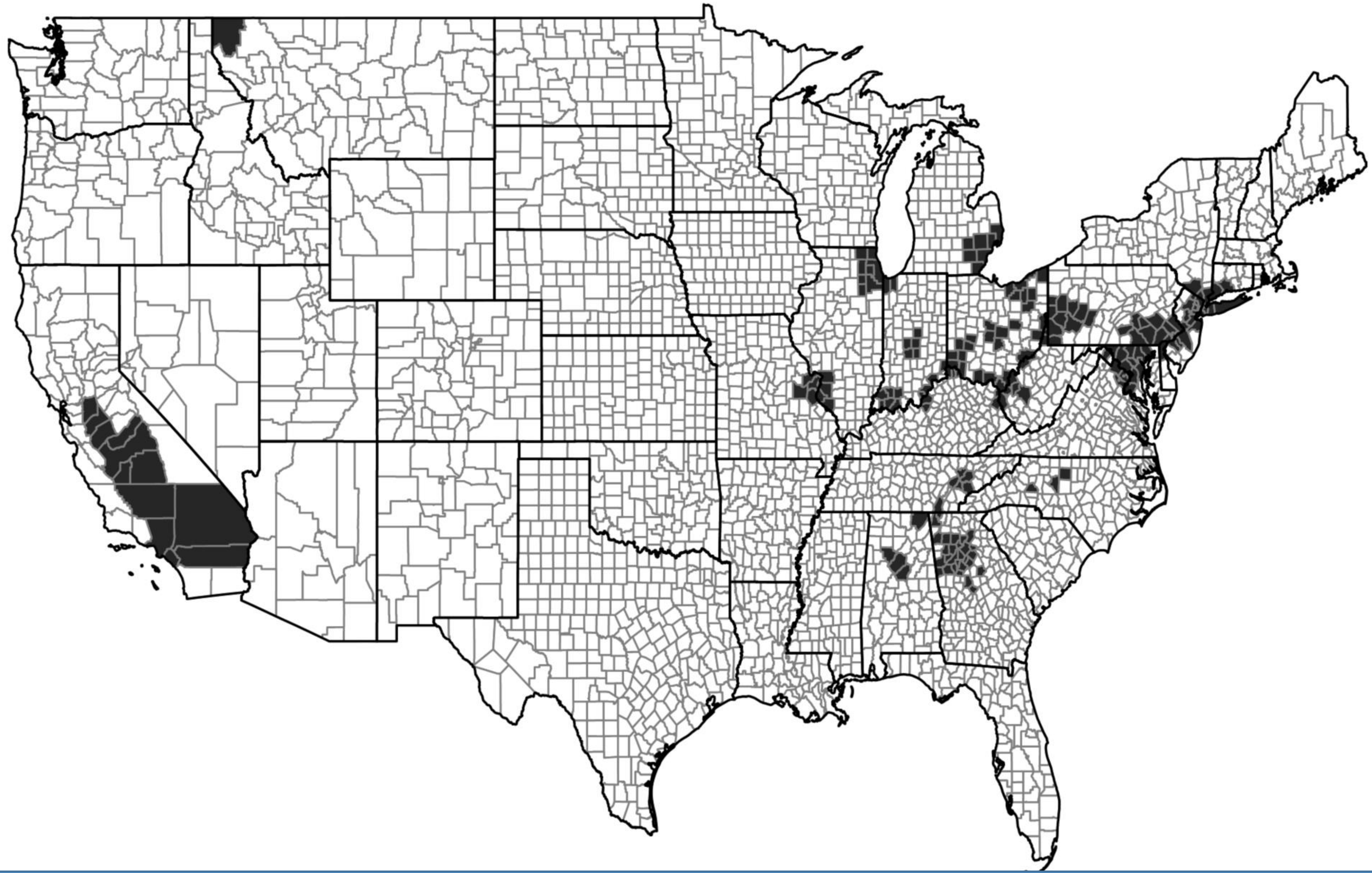
Quasi-experimental approach

- Exploit exogenous event
  - Event caused by external factor: policy, nature, etc.
  - Quasi-random assignment into **treatment** and **control** groups
  - Involves “shoe-leather” to convince of:
    - Ex ante random assignment
    - Ex post no response to assignment
- Successfully used in social sciences: minimum wage, military deployment, school quality, health insurance, etc.
- Despite origins in epidemiology, less used

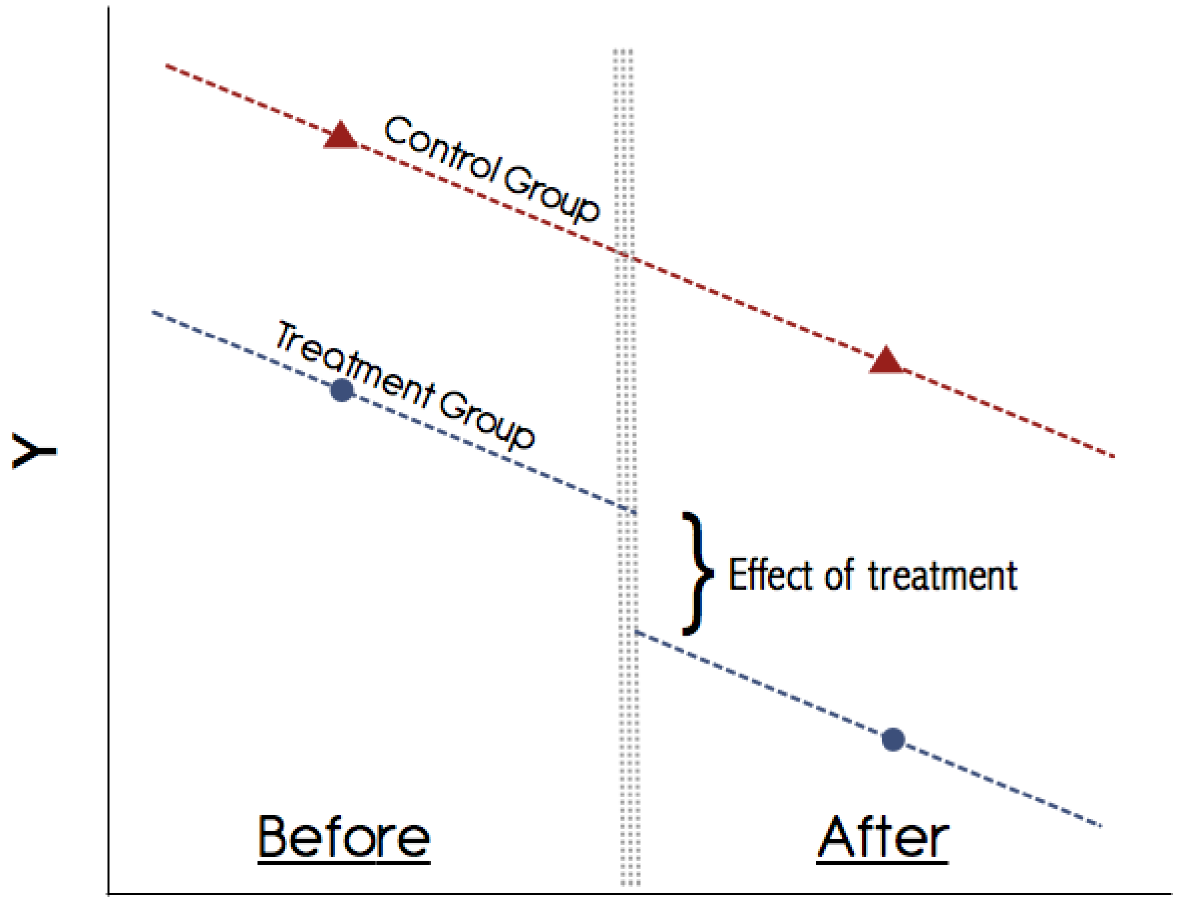
CAAA and attainment status

- Ruling in 1997
  - $PM_{2.5}$ AQS: 15.0 μg/m^3
  - Annual mean, averaged over 3 years
- Promulgated in 2005
  - Based on 2001-3
  - Classify into attainment (≤15) vs. non-attainment (>15)
  - Non-attainment: binding regulations to lower $PM_{2.5}$
- Quasi-experiment
  - **Treatment**: non-attainment; **control**: attainment
  - $PM_{2.5}$ exogenously decreases in treatment (relative to control)
  - Mortality exogenously decreases in treatment (relative to control)

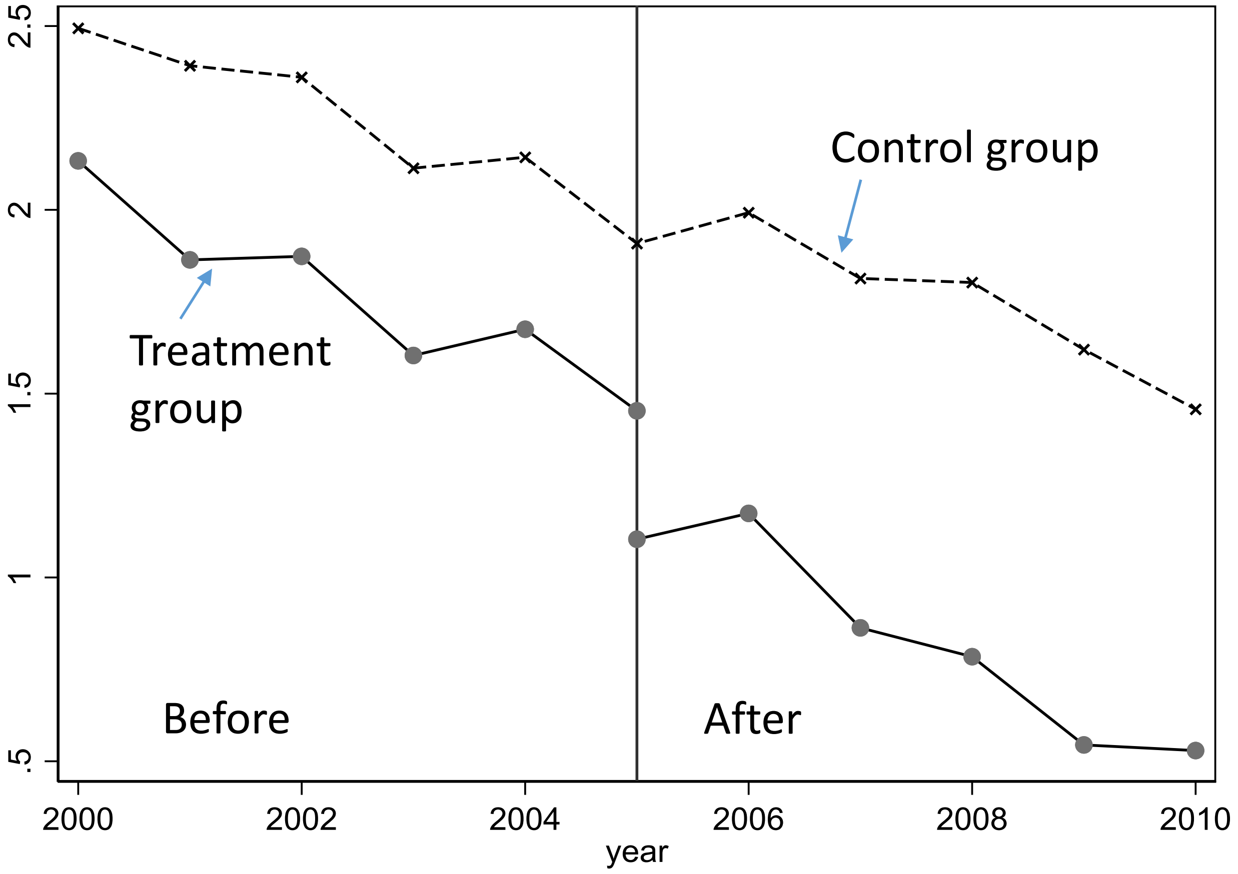
Figure 1. Map of Nonattainment Counties



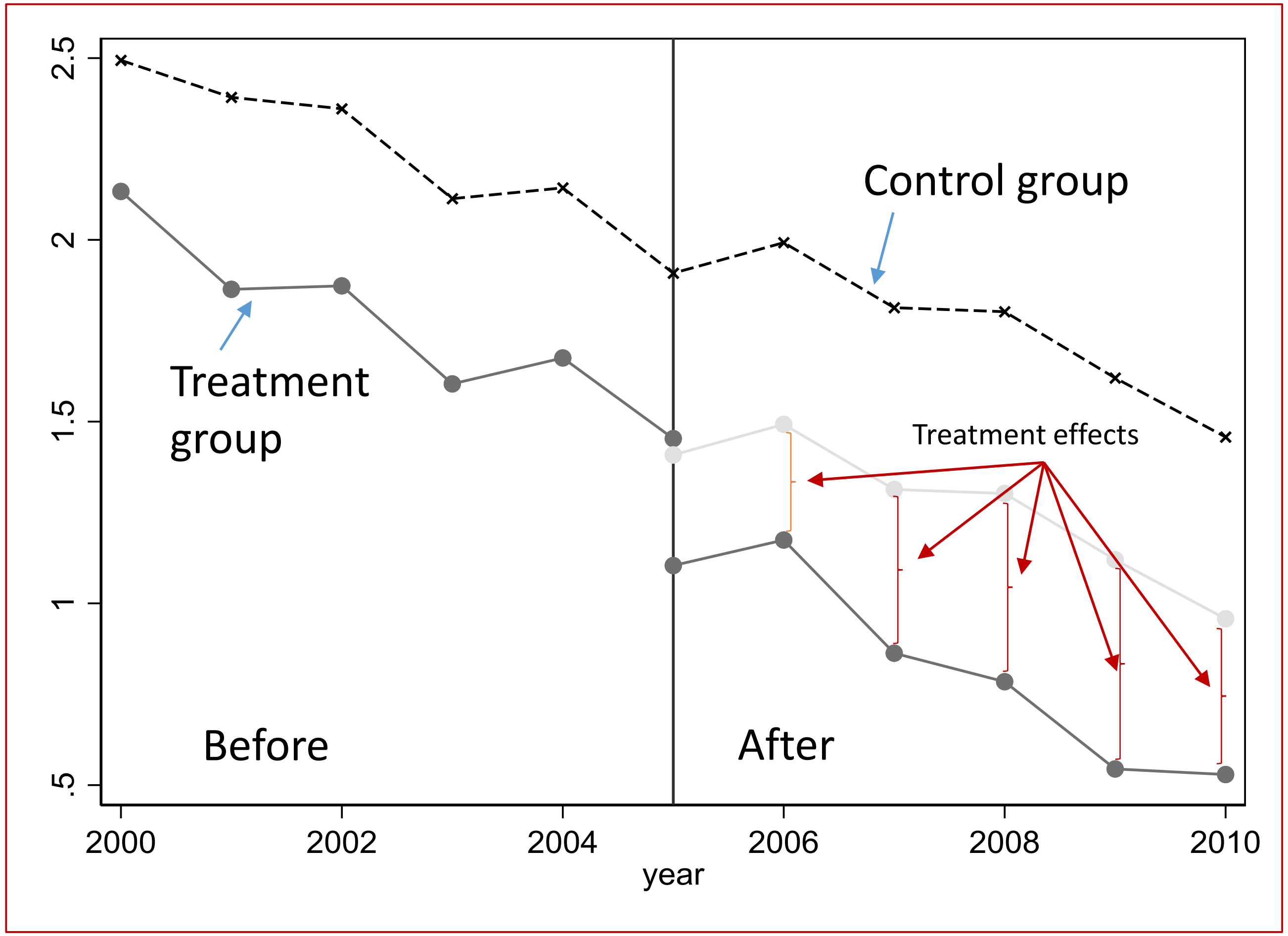
Difference in differences (DiD) example



Event study DiD example



Event study DiD example



Estimating equations

Standard DiD

(1) $\text{outcome}_{ct} = \beta(\text{Treatment})*(\text{Year} \geq 2005) + \alpha_c + \kappa_t + \varepsilon_{ct}$

β = DiD estimate

"Event study" DiD

(2) $\text{outcome}_{ct} = \Sigma_{t \neq 2005}\, \delta_t(\text{Treatment})*(\text{Year} = t) + \alpha_c + \kappa_t + \varepsilon_{ct}$

δ_t = event study estimates

- Test for pre-trends
- Allow policy effect to vary over time

<u>Notes:</u>

Outcome = $PM_{2.5}$ or log(mortality rate)

Treatment = 1 if non-attainment; 0 if attainment

Cluster on county

Estimate via OLS; mortality regressions weighted

Data

- Mortality
  - Medicare beneficiaries
  - Date of death, age, sex, FIPS code of residence
- Pollution
  - 24-hour average $PM_{2.5}$
  - Averaged to county level
- Attainment status: EPA Green Book
- Population by age: SEER
- Weather: daily max/min temp., rainfall (GHCND)
- Economic outcomes: income pc, share employed (BEA)
- Migration data: returns and exemptions (IRS)

Table 1. DiD estimates for $PM_{2.5}$ and mortality

	1	2
Dependent variable	$PM_{2.5}$	Log Mortality
DiD estimate	-1.5320** [0.0928]	-0.0099* [0.0041]
Observations	7825	7817
R-squared	0.877	0.952

Figure 2. Event study estimates for $PM_{2.5}$

Figure 3. Log mortality rates for treatment and control counties

Figure 4. Event study results for mortality rate

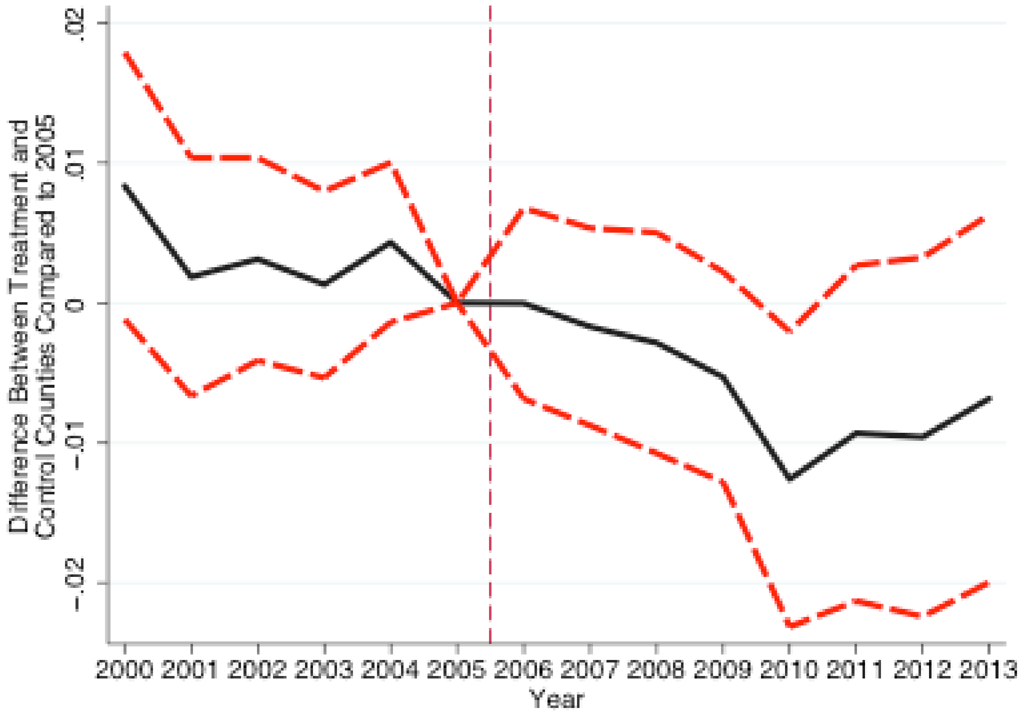


Table 1. Heterogeneity by sex & age

7	8	9
Log Male Mortality	Log Female Mortality	Log Mortality Over 75
-0.0045	-0.0122**	-0.0113**
[0.0041]	[0.0047]	[0.0042]
7814	7816	7817
0.935	0.931	0.918

Study limitations: Did other things change at the same time?

- Table 1. Add economic, weather, age controls

2	3	4
Log Mortality	Log Mortality	Log Age-Adjusted Mortality
-0.0099* [0.0041]	-0.0086* [0.0041]	-0.0090* [0.0040]
7817	7817	7817
0.952	0.953	0.953

Study limitations: Did other things change at the same time?

- Table 2. Migration

	1	2
Dependent variable	Net Returns	Net Exemptions
DiD estimate	-674.90 [457.46	-1584.54 [995.16]
Observations	7816	7816
R-squared	0.42	0.44

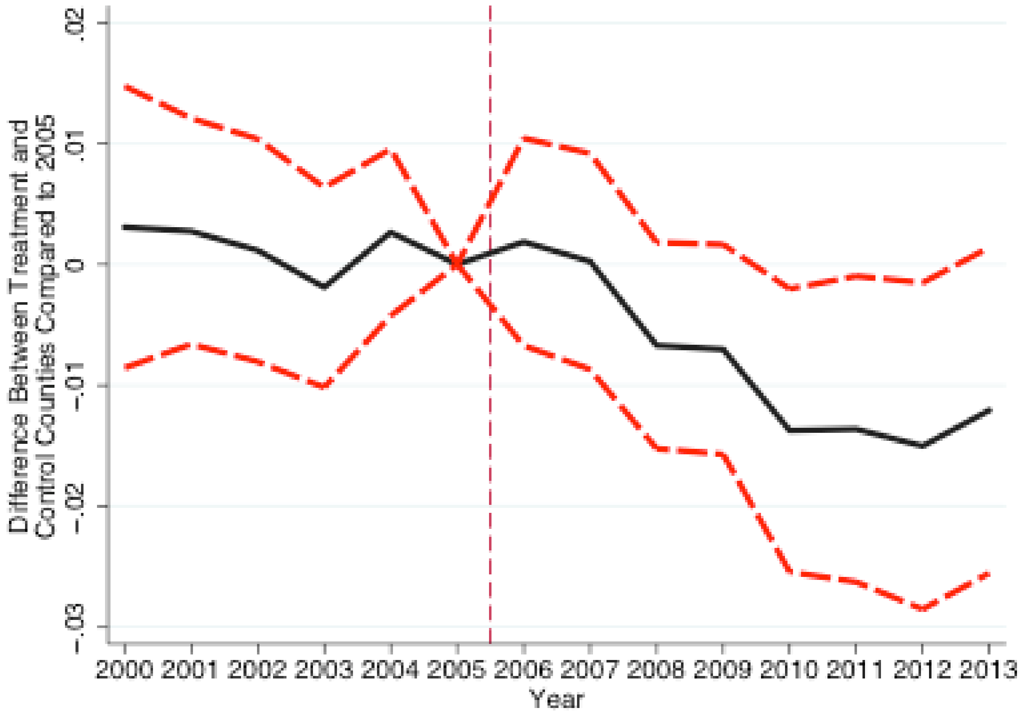
Study limitations: SUTVA

- Pollution in treatment county affects outcome in control county
- Potential solution: nearest neighbor matching based on propensity score
  - Propensity score
    - Estimate probability county is treatment group (vs. control group)
    - Controls include mortality rates in years prior to policy change
  - Match treatment county to control county with closest p-score
  - Estimate DiD on this sample

Table 1. DiD estimates using propensity score

	Nearest neighbor	**Common support**
DiD	-0.0106*	-0.0090*
	[0.0044]	[0.0042]
Obs.	3,368	6,906
R-sq	0.955	0.963

Figure 5. Event Study Results for Mortality Rate using Nearest Neighbor Matching



Discussion

- AQS for $PM_{2.5}$ causally
  - Reduced $PM_{2.5}$ by 1.53 µg/m^3
  - Reduced mortality by 0.9%
  - Robust to various assumptions

→$PM_{2.5}$ reduces mortality
  - Combine the two estimates: 1 µg/m^3 decrease in $PM_{2.5}$ reduces mortality by 0.6%
  - Caveat: other pollutants may have changed

- Conclusion: AQS for $PM_{2.5}$ reduced mortality, (very) likely through changes in $PM_{2.5}$