The Long-run Effect of Air Pollution on Survival

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How bad is air pollution for adult health?

- Air pollution harms health in both the short and long run

- But, the magnitude of the effect remains uncertain
  - Observational estimates are prone to bias
  - Quasi-experimental studies focus on short-run effects

- Identifying the long-run effect of chronic exposure is hard
  - Limited data on long-run outcomes
  - Variation in long-run exposure hard to find

How do we address these challenges?

1. Use variation in wind direction as instrument for daily pollution
   - Trace out mortality patterns up to one month following acute exposure
   - Limited to short-run effects of acute exposure

2. Integrate empirical estimates into dynamic production model of health
   - Can be internally validated using quasi-experimental estimates

Treatment exposure	Short-run outcomes	Long-run outcomes
Acute	Empirical estimates	Model
Chronic	-	Model

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Research questions

- Setting: United States population, 1972–1988
- Pollutant: sulfur dioxide (SO_2)

1. What is the short-run causal effect of acute (one-day) exposure to SO_2?
   - Instrumental variables research design
   - Main outcome: monthly (28-day) mortality

2. What is the long-run effect of chronic exposure to SO_2?
   - Production model of health from Lleras-Muney and Moreau (2022)
   - Main outcome: life expectancy

Main results

- A 1-day, 10% increase in SO_2 increases same-day mortality by 0.3 percent

- In the month following exposure:
    - Cumulative effect for cancer deaths falls to zero ("mortality displacement")
    - Cumulative effect for other diseases more than triples ("accelerated aging")
    - On net, cumulative mortality more than doubles

- Benefit of reducing lifetime SO_2 exposure by 10% is 1.2 years of extra life
    - 90% of benefits occur after age 50

Contributions to the literature

- Framework for estimating long-run survival effects of chronic exposure
  - Model calculations differ from IV extrapolation
  - Approach is similar in spirit to Athey, Chetty, and Imbens (2020)

- Health effects of air pollution (Chay and Greenstone 2003; Currie and Neidell 2005; Schlenker and Walker 2016; Hollingsworth and Rudik 2021; Alexander and Schwandt 2022; Heo, Ito, and Kotamarthi 2023)
  - We are the largest quasi-experimental study (17 years, 18 million deaths)
  - We focus on mortality dynamics

Background and Data

EPA regulates six air pollutants

- Carbon monoxide (CO)
- Ozone (O_3)
- Nitrogen dioxide (NO_2)
- Lead
- Particulate matter (PM)
- Sulfur dioxide (SO_2)

- We focus on SO_2, which is well-measured during our 1972–1988 time period
  - Regulated at the daily and annual levels

SO_2 has immediate and delayed effects

- Direct exposure to SO_2 impairs respiratory function
- SO_2 leads to formation of sulfates, a component of PM 2.5 (fine particulates)
  - Acute exposure to PM 2.5 causes premature death
- Chronic exposure to air pollution associated with "accelerated aging"
  - Risk factors for cardiovascular disease (eg, coronary artery calcification)
  - Initiation and promotion of lung cancer

Daily environmental data

- Data on SO_2 obtained from EPA site monitors
  - Not available for all counties $\rightarrow$ limiting factor in the final size of our sample

- Temperature and precipitation obtained from Schlenker and Roberts (2009)

- Wind direction and wind speed obtained from Japan Meteorological Agency

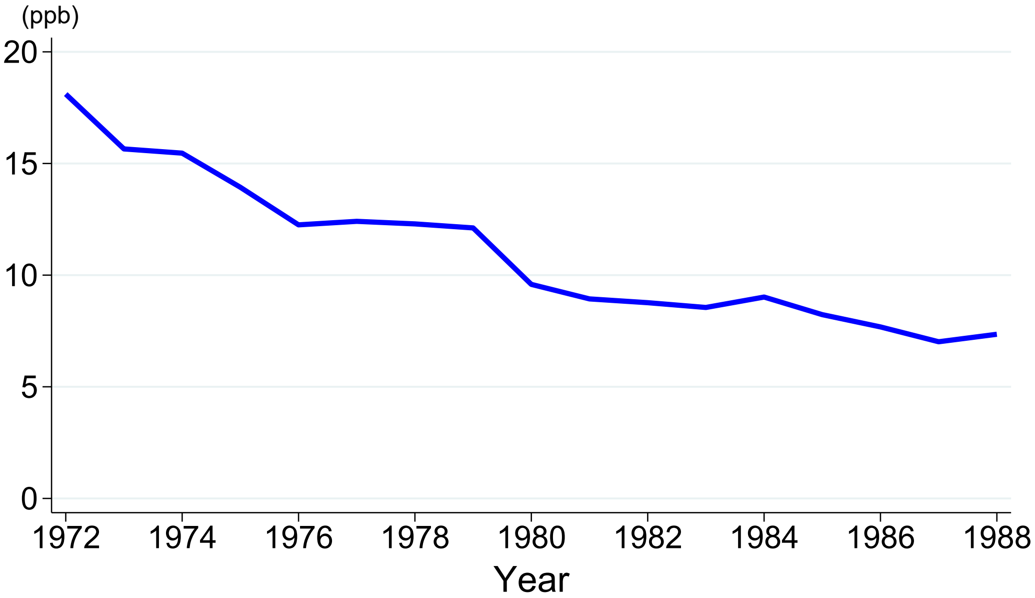
- All data are aggregated to the county-day level

Daily mortality data

- National Vital Statistics, 1972–1988
  - Exact date of death
  - County of occurrence
  - Cause of death
  - Age, sex, and race of decedent

- Merge with environmental data at the county-day level
  - Main specification includes 2.03 million county-day observations

SO_2 levels are declining during our sample period



Summary statistics

	(1)	(2)	(3)
	Mean	Std. Dev.	Observations
A. Pollution outcomes			
SO_2, ppb	8.96	12.62	2,032,338
NO_2, ppb	21.25	15.60	792,784
CO, ppm	1.64	1.37	848,067
Ozone, ppb	25.53	13.69	669,261
TSP, μg/m^3	63.11	40.19	628,932
B. One-day mortality rate outcomes			
All-cause mortality, deaths per million	24.70	24.32	2,032,338
Cardiovascular	12.21	16.04	2,032,338
Cancer	5.15	9.16	2,032,338
Other	5.45	10.02	2,032,338
External	1.89	7.99	2,032,338

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Empirical Analysis

Short-run effects of acute exposure

Empirical strategy: instrumental variables (2SLS)

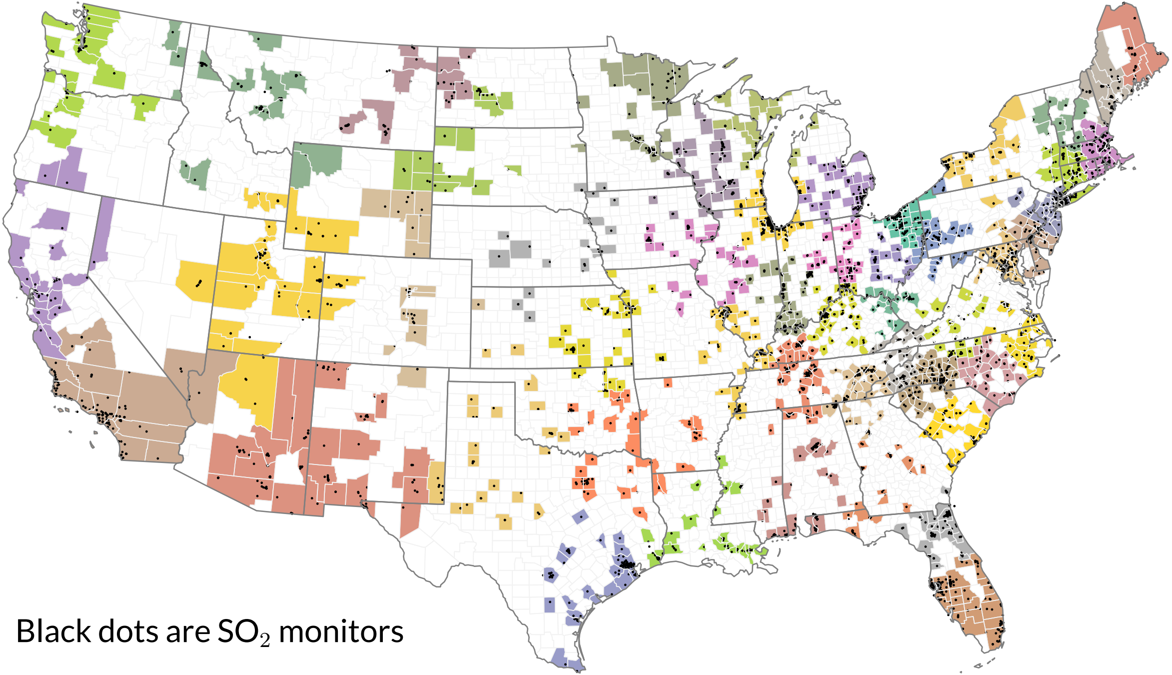
- Wind carries pollutants over long distances

- Key insight: no need to isolate the pollution source! (Deryugina et al. 2019)
  - Maximizes the size of our estimation sample

- Identifying assumption:
  - Wind direction unrelated to health except through pollution

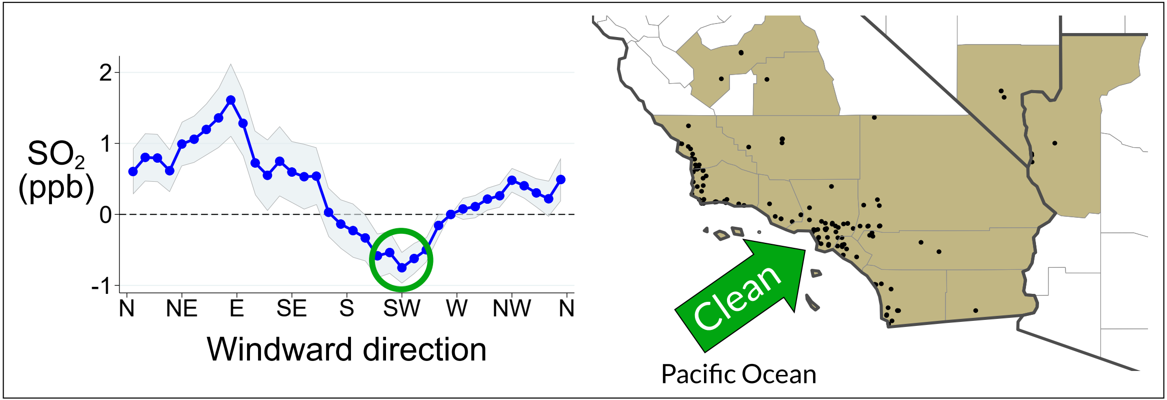
How do we construct our instruments?

- Use clustering algorithm to assign pollution monitors to 50 regional groups
- First stage is group-specific relationship between wind direction and pollution
- Allow pollution transport patterns to vary across groups
  - Wind blowing from west has different effect in California than in Massachusetts



Black dots are SO_2 monitors

Wind direction and SO_2 in Southern California area



Blue shading depicts 95% confidence intervals
Black dots on map are SO_2 monitors

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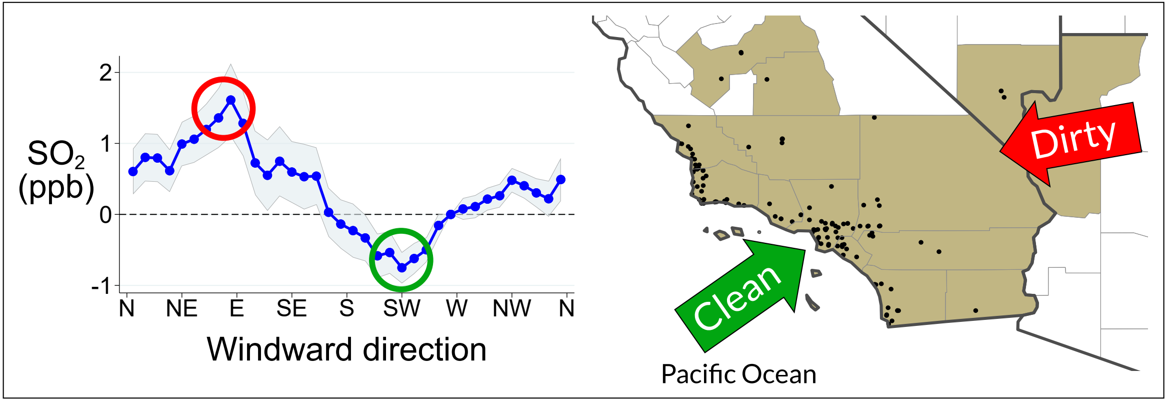

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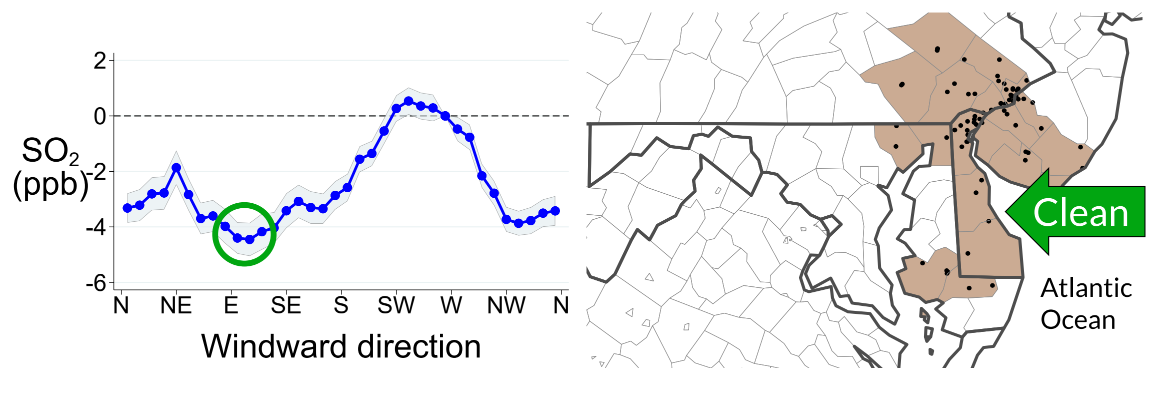
Wind direction and SO_2 in Greater Philadelphia area



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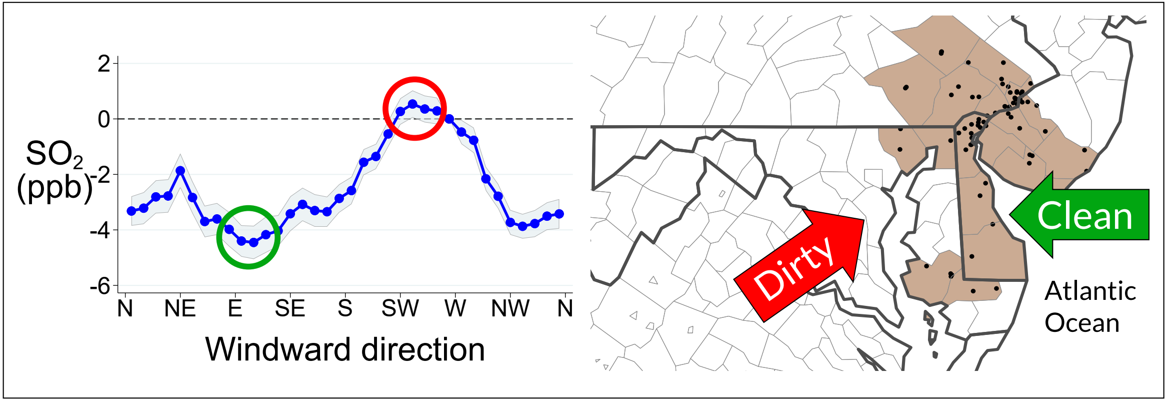
Wind direction and SO_2 in Greater Philadelphia area



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First stage: excluded instrument is wind direction

$$\text{SO2}_{cd} = \sum_{g=1}^{50} \boldsymbol{f^g(\theta_{cd})} + X_{cd}^{k\,\prime}\delta + \alpha_{cm} + \alpha_{my} + \varepsilon_{cd}$$

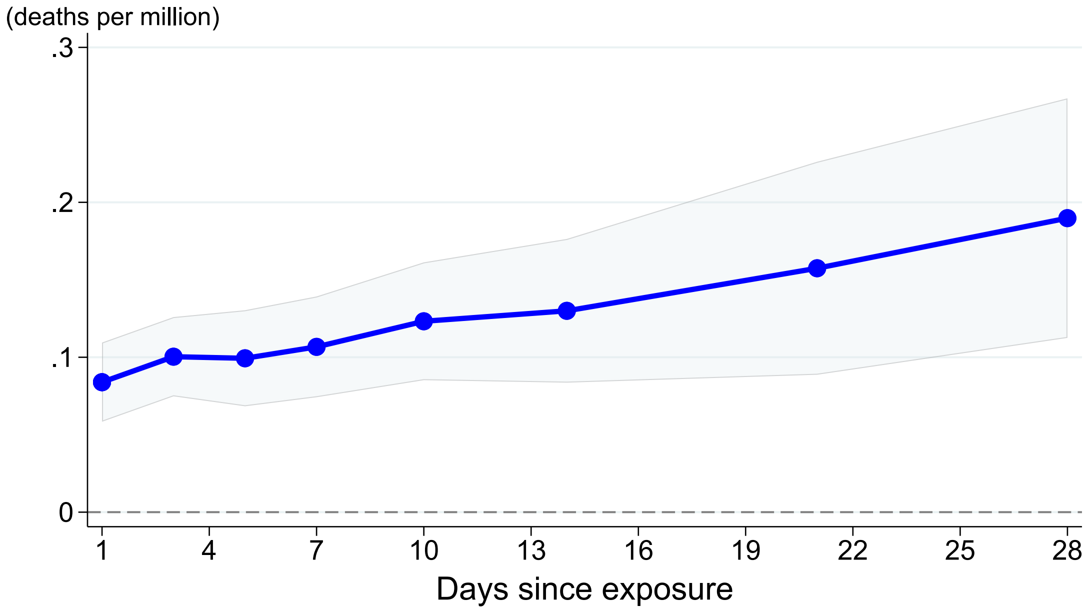
- Dependent variable is level of SO_2 in county c on day d
- Effect of wind direction, θ_{cd}, varies across 50 geographic groups, g
- Consider two functional forms for $\boldsymbol{f^g(\theta_{cd})}$
  - Non-parametric 10-degree bins (1750 instruments)
  - Parametric sin function (100 instruments, preferred specification) ▸ Example

Second-stage regression

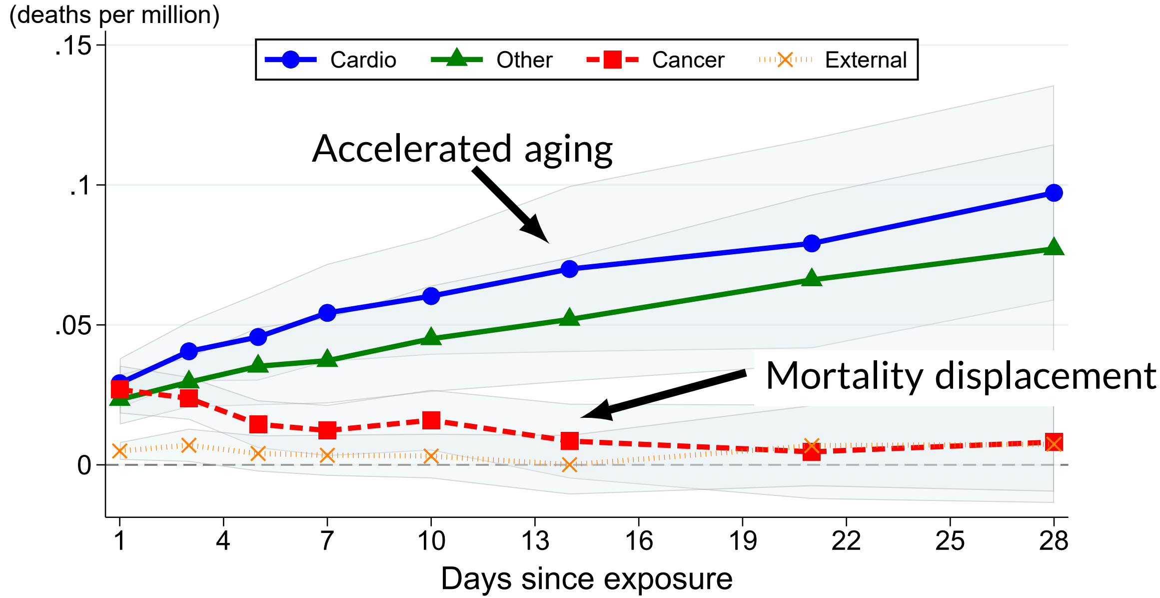
$$Y_{cd}^{k} = \beta^{k} \widehat{\text{SO2}}_{cd} + X_{cd}^{k\,\prime}\delta + \alpha_{cm} + \alpha_{my} + \varepsilon_{cd}$$

- Estimate effect of 1-day exposure on k-day mortality rate (up to $k = 28$)
- Control for county-by-month (α_{cm}) and month-by-year (α_{my}) fixed effects
- Flexibly control for max temperature, precipitation, and wind speed
- Cluster standard errors at the county level, weight by county population

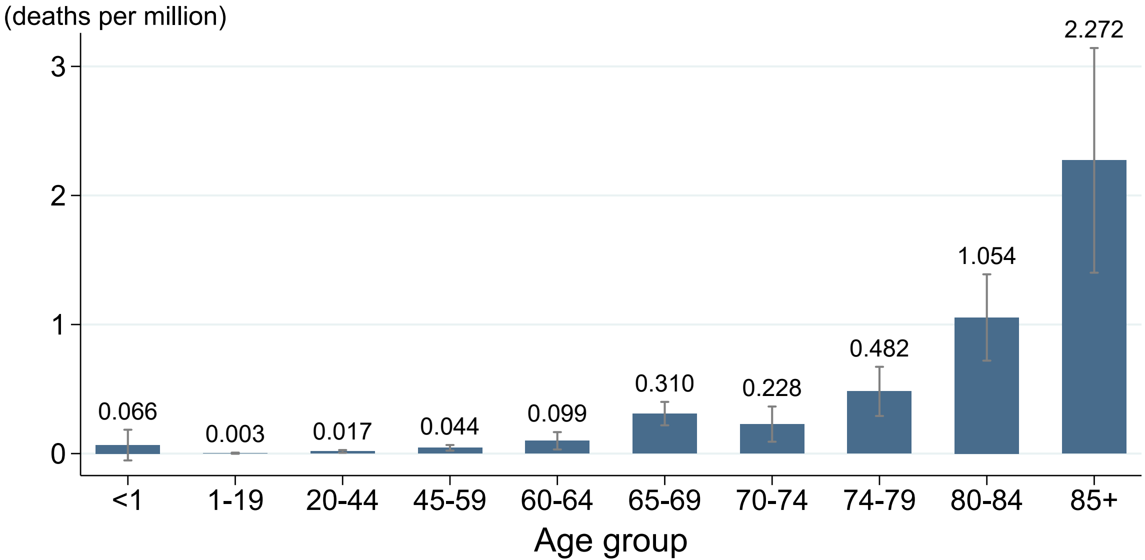
Cumulative mortality effect grows over time



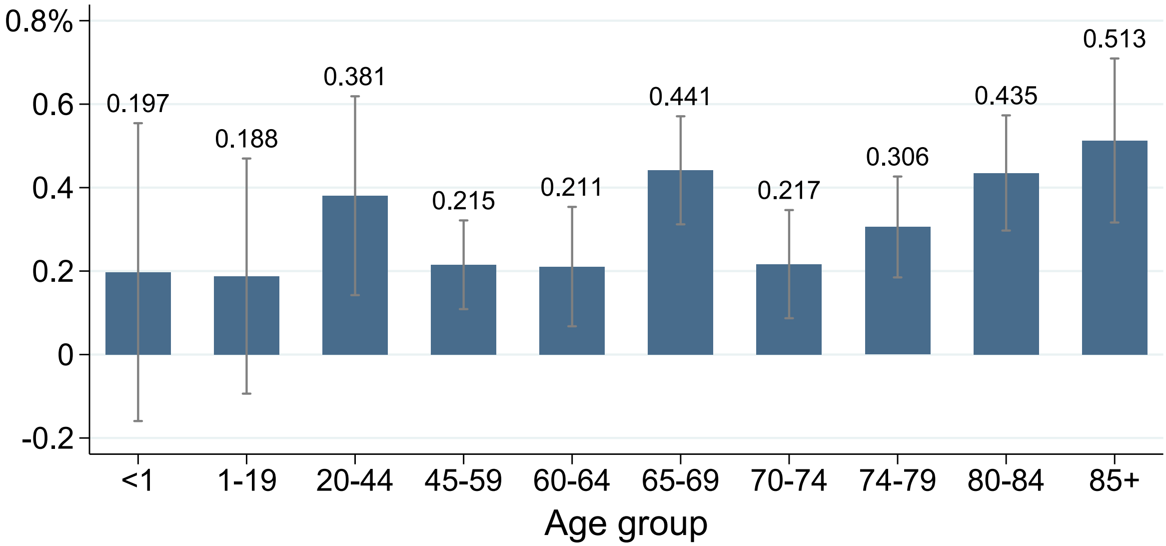
Divergent patterns by cause of death



1-day mortality by age group (deaths per million)



1-day mortality by age group (relative effect)



Alternative specifications and robustness checks

- Accounting for other air pollutants ▸ Table
- Sensitivity check: alternative weather controls ▸ Table
- Falsification test: SO_2 on day t has no effect on mortality on day $t-1$ ▸ Table
- Placebo test: random wind direction produce weak first stage ($F \leq 2$) ▸ Table

Long-run Survival

Model: Lleras-Muney and Moreau (2022)

Health capital for individual i at age t:

$$H_{it} = H_{i,t-1} - \underbrace{\delta t^{\alpha}}_{\text{depreciation}} + I + \varepsilon_{it}$$

where:

$$H_{i0} = H_{i0}^{*} \sim N(\mu_H, 1)$$
$$\varepsilon_{it} \sim N(0, \sigma_{\varepsilon}^{2})$$

Model: Lleras-Muney and Moreau (2022)

$$H_{it} = H_{i,t-1} - \delta t^{\alpha} + I + \varepsilon_{it}$$

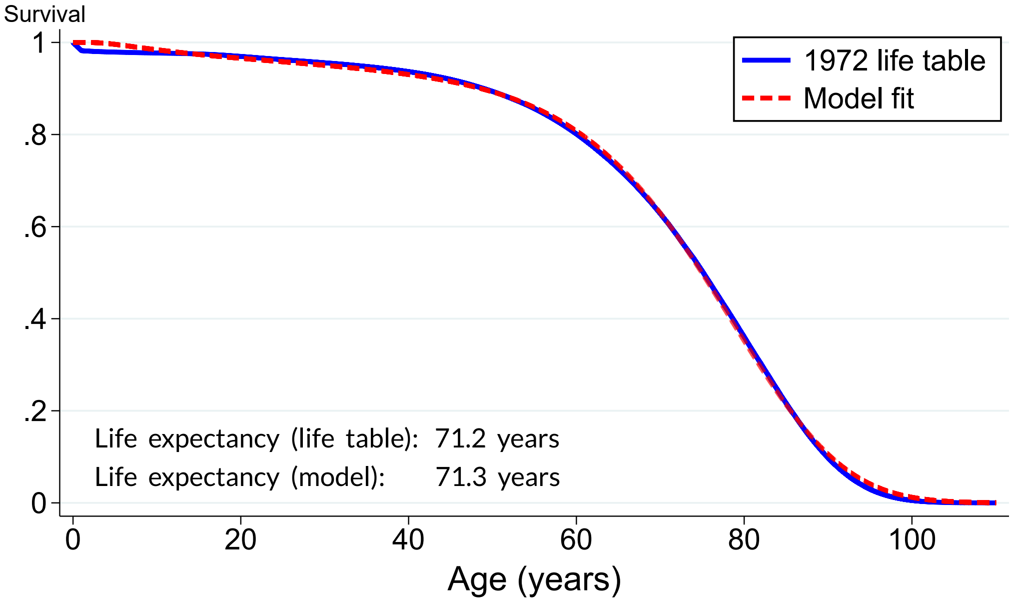
- Death occurs when health capital falls below threshold $\underline{H} = 0$:

$$D_{i0} = 1\left[H_{i0} < \underline{H}\right],$$
$$D_{it} = 1\left[H_{it} < \underline{H} \middle| D_{i,t-1} = 0\right],\ t > 0$$

- Simulate model for N agents $\rightarrow$ survival curve

- Model captures a variety of real-world mortality dynamics
  - Mortality displacement
  - Accelerated aging

Calibrate baseline parameters using 1972 period life table



Key structural assumption for incorporating IV estimates

- Effect of pollution on model parameters depends only on current exposure
  - Effect on parameters is same for old and young
  - Effect on parameters is independent of exposure history

- Thus, we can calibrate the effect of exposure using any age group

- Testable implication: calibration from one age predicts survival for other ages

Calibrate using 1-day IV estimates

$$H_{it} = H_{i,t-1} - \delta t^{\alpha} + I + \varepsilon_{it}$$
$$D_{it} = 1\left[H_{it} < \underline{\text{H}} \,\middle|\, D_{i,t-1} = 0\right],\ t > 0$$

Acute exposure affects mortality through two channels:

1. Raises depreciation for 1 day, $\delta \rightarrow \widetilde{\delta}$
   - accelerated aging effect
   - calibrate using 1-day non-cancer IV estimate

2. Raises death threshold for 1 day, $\underline{\text{H}} \rightarrow \widetilde{\underline{\text{H}}}$
   - mortality displacement
   - calibrate using 1-day cancer IV estimate

Calibration steps for age group a

1. Solve for $\underline{\widetilde{\mathrm{H}}}_a$ such that 1-day mortality increases by $\widehat{\beta}^1_{a,cancer}$

2. Solve for $\widetilde{\delta}_a$ such that 1-day mortality effect of $\{\underline{\widetilde{\mathrm{H}}}_a, \widetilde{\delta}_a\}$ equals $\widehat{\beta}^1_{a,all}$

Do calibration for older age groups only (65 and over)

Any pair $\{\underline{\widetilde{\mathrm{H}}}_a, \widetilde{\delta}_a\}$ can be used for predictions
$\rightarrow$ Preferred estimate uses average of all older age groups

Example: ages 65–69

	(1)	(2)
Age group	All causes	Cancer-related causes
65–69	0.31**	0.17**
	(0.046)	(0.028)
70–74	0.23**	0.14**
	(0.070)	(0.034)
75–79	0.48**	0.13**
	(0.097)	(0.040)
80–84	1.1**	0.18**
	(0.17)	(0.065)
85+	2.3**	0.17*
	(0.44)	(0.084)

Notes: Dependent variable is deaths per million on the day of exposure.

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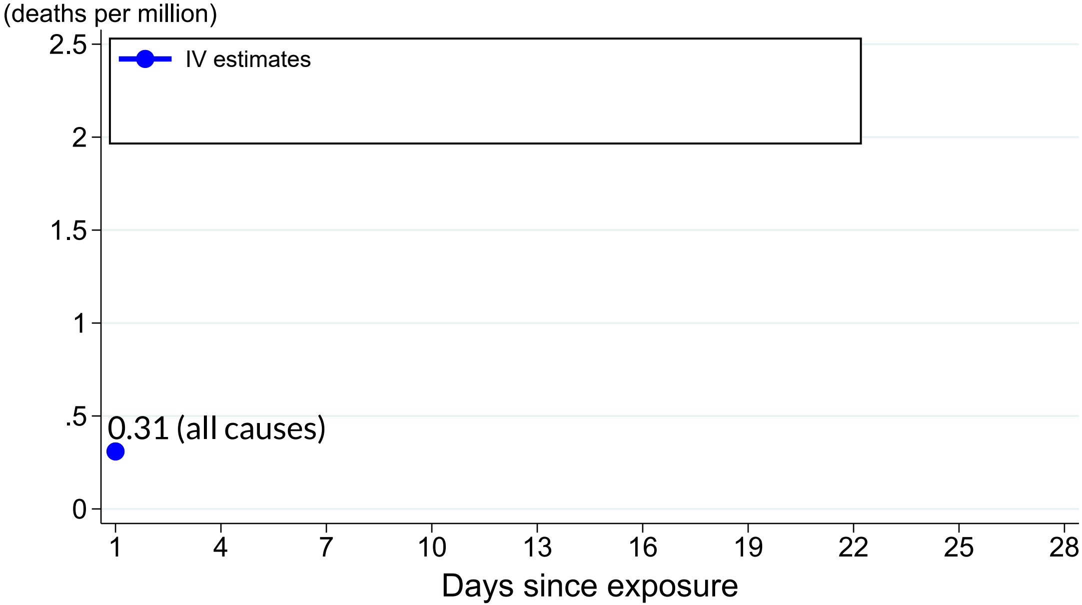

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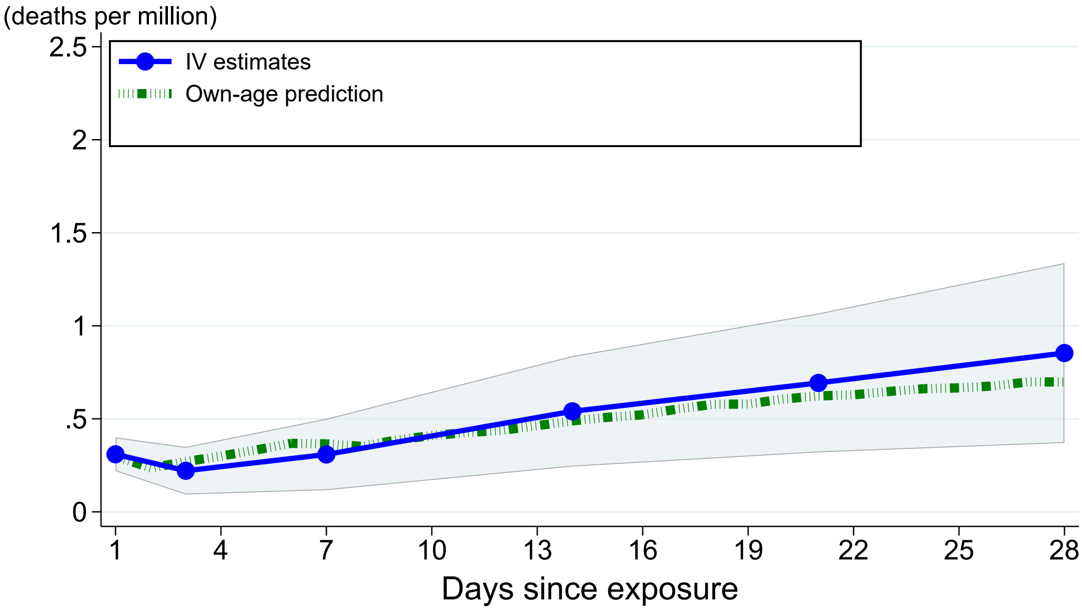

“Leave-one-out” validation: calibrate using other ages

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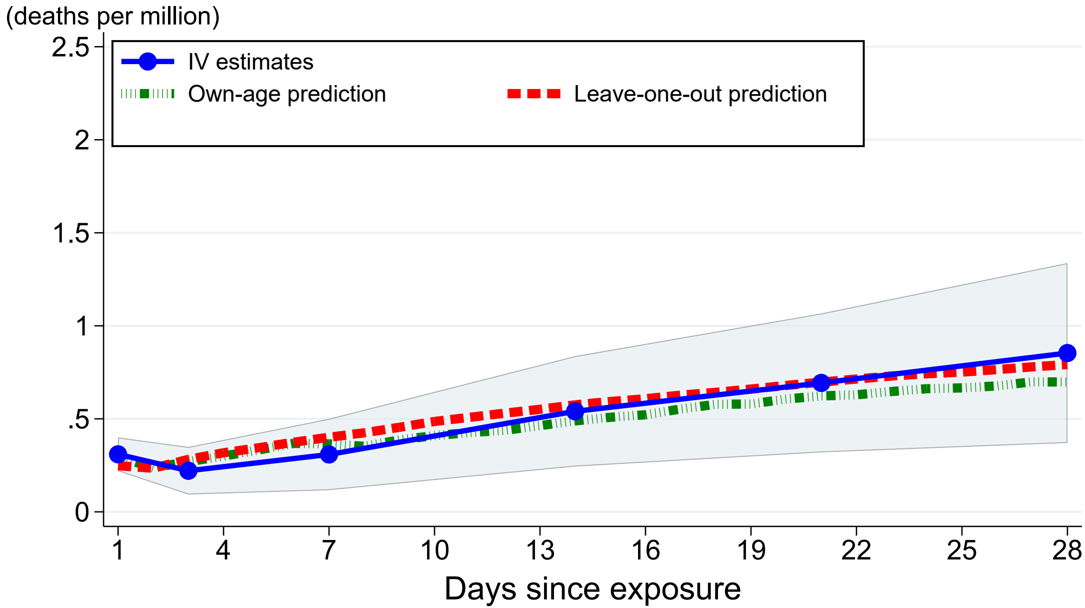

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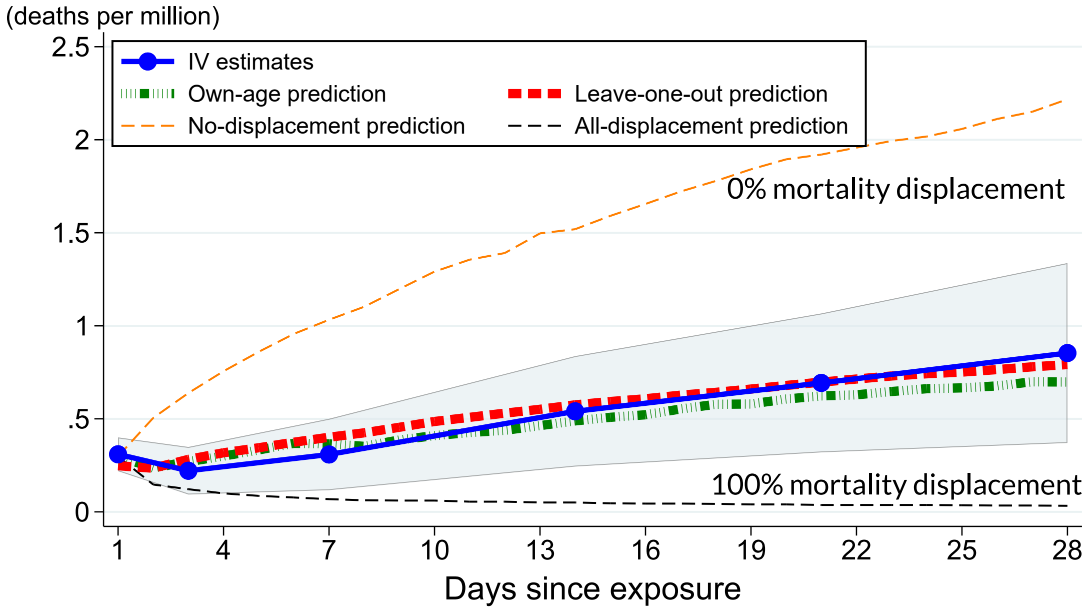
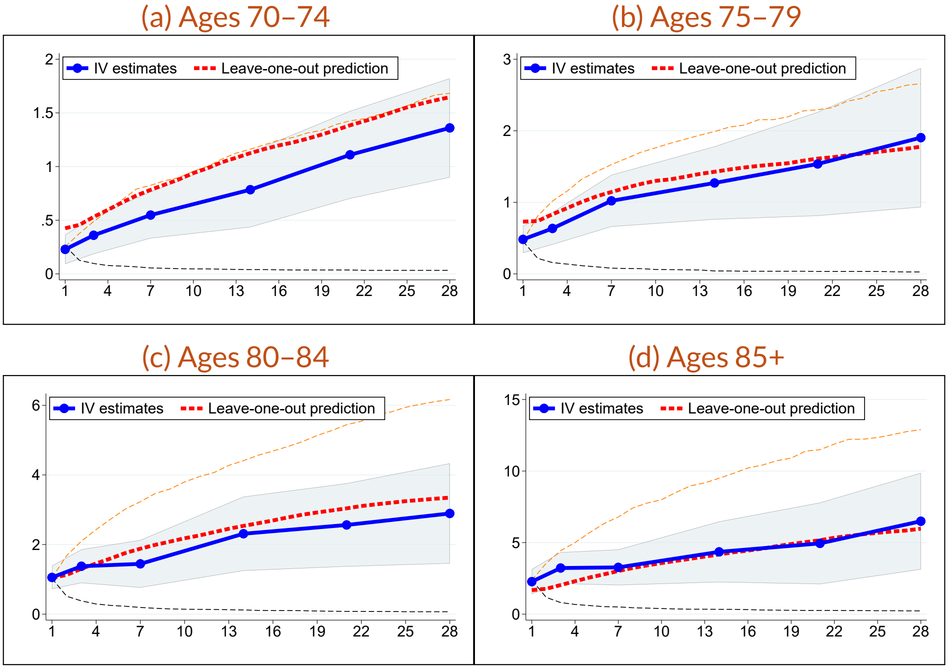
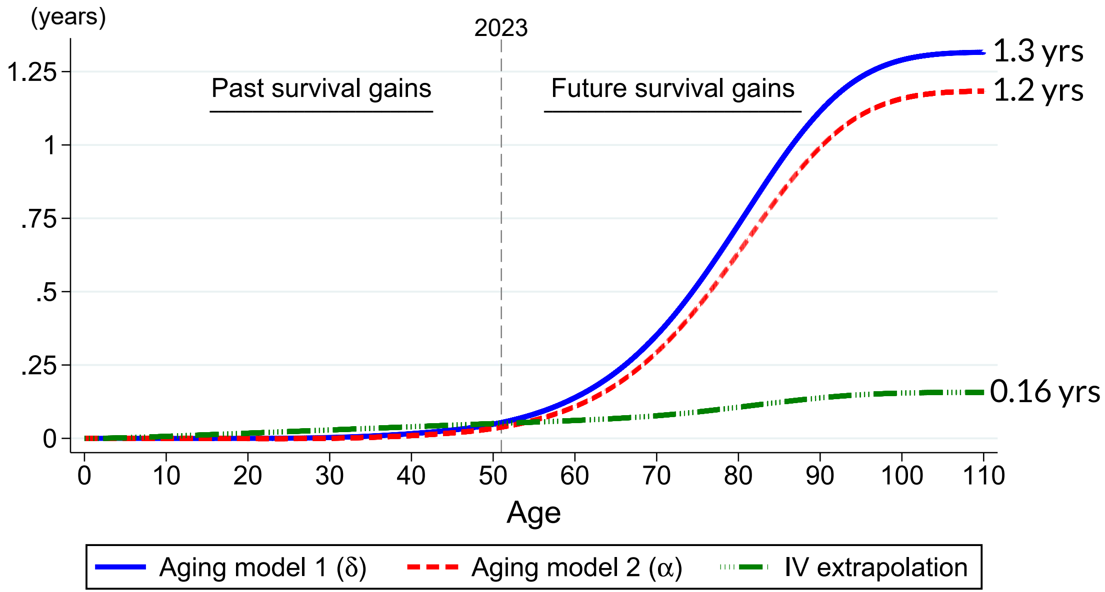



(a) Ages 70–74
IV estimates
Leave-one-out prediction
0
.5
1
1.5
2
1
4
7
10
13
16
19
22
25
28
(b) Ages 75–79
IV estimates
Leave-one-out prediction
0
1
2
3
1
4
7
10
13
16
19
22
25
28
(c) Ages 80–84
IV estimates
Leave-one-out prediction
0
2
4
6
1
4
7
10
13
16
19
22
25
28
(d) Ages 85+
IV estimates
Leave-one-out prediction
0
5
10
15
1
4
7
10
13
16
19
22
25
28

Survival benefit of 1-unit reduction in chronic exposure



Interpreting long-run survival estimates

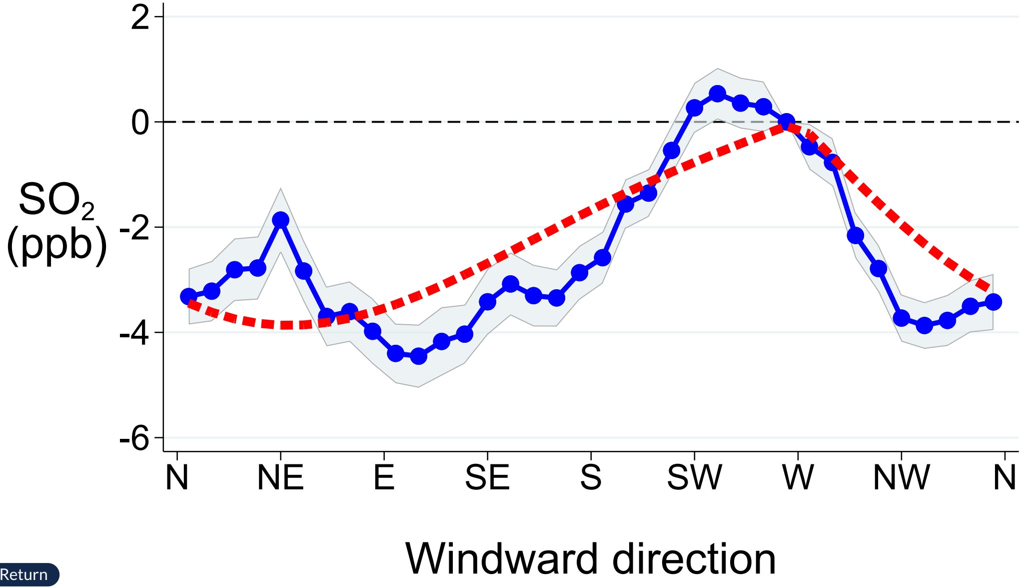
- Uncertainty in IV estimates produces uncertainty in long-run estimates
    - 5th and 95th percentiles from bootstrap yield range of $[0.3, 2.2]$ years
- SO_2 estimates may also include effects from particulate matter
- Survival model holds behavior fixed
    - We interpret estimates as gross benefits (Graff Zivin and Neidell 2012; Currie et al. 2014)

Conclusion

- Air pollution causes mortality displacement and accelerating aging
- Permanent, 10% reduction in exposure improves life expectancy by 1.2 yrs
  - 7 times larger than extrapolation of short-run estimate
  - Benefits concentrated in ages 50+

The End

First stage: parametric sin fit for Greater Philadelphia area



◂ Return

Sensitivity check: alternative weather controls

	(1)	(2)	(3)	(4)
SO_2, parts per billion	0.098**	0.084**	0.084**	0.085**
	(0.014)	(0.013)	(0.013)	(0.012)
First-stage F-statistic	32	42	68	33
Mean outcome	25	25	25	25
Sample size	2,032,340	2,032,338	2,032,272	2,031,752
Weather controls				
Baseline weather variables		X	X	X
Minimum temperature variables			X	X
More granular bins				X

Notes: Dependent variable is 1-day mortality (deaths per million).

Return

IV estimates: accounting for multiple air pollutants (1/2)

	(1)	(2)	(3)	(4)	(5)	(6)
SO_2, ppb	0.084**	0.060**	0.065**	0.066**	0.059**	0.064**
	(0.012)	(0.013)	(0.014)	(0.012)	(0.012)	(0.014)
TSP, μg/m^3		0.012**	0.014**	0.014**	0.013**	0.015**
		(0.0036)	(0.0037)	(0.0033)	(0.0040)	(0.0035)
NO_2, ppb			−0.014			0.0023
			(0.013)			(0.017)
Ozone, ppb				−0.044*		−0.046*
				(0.021)		(0.022)
CO, ppm					−0.20	−0.24
					(0.17)	(0.20)
First-stage F-statistic	81	21	17	11	20	10
Mean outcome	27	27	27	27	27	27
Sample size	78,946	78,946	78,946	78,946	78,946	78,946

Notes: Dependent variable is 1-day mortality (deaths per million).

IV estimates: accounting for multiple air pollutants (2/2)

	(1)	(2)
SO_2, ppb	0.079**	0.035*
	(0.014)	(0.015)
TSP, μg/m^3		0.019**
		(0.0045)
First-stage F-statistic	96	50
Mean outcome	25	25
Sample size	627,304	627,304

Notes: Dependent variable is 1-day mortality (deaths per million). A */** indicates significance at the 5%/1% level. "TSP" is total suspended particulates.

Return

Placebo and falsification tests

	(1)	(2)	(3)	(4)
SO_2, ppb	–0.079	0.18	–0.041	
	(0.062)	(0.23)	(0.49)	
SO_2 on day $t+1$, ppb				–0.0036
				(0.0048)
Outcome window, days	1	7	28	1
First-stage F-statistic	2.0	1.9	1.9	28
Mean outcome	25	173	691	25
Sample size	2,023,456	2,023,435	2,023,369	2,031,165
Placebo test	X	X	X	
Falsification test				X

Notes: Dependent variable is number of deaths per million people over a window of 1, 7, or 28 days.

Return