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 90 days 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), a precursor to fine particulate matter ($PM_{2.5}$)

1. What is the short-run causal effect of acute (one-day) exposure to SO_2?
   - Instrumental variables research design
   - Main outcome: mortality up to 90 days since exposure

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 at birth

Contributions to the literature

- Framework for estimating long-run survival effects of chronic exposure
  - Combines quasi-experimental and structural methods (Todd and Wolpin, 2023)
  - Our model estimates differ substantially from simple extrapolation

- Health effects of air pollution (e.g., Chay and Greenstone 2003; Currie and Neidell 2005; Chen et al. 2013; Knittel, Miller and Sanders 2016; Schlenker and Walker 2016; Deschênes, Greenstone and Shapiro 2017; Ebenstein et al. 2017; Anderson 2020; Barreca, Neidell and Sanders 2021; Hollingsworth, Konisky and Zirogiannis 2021; Alexander and Schwandt 2022; Colmer and Voorheis 2025; Heo, Ito and Kotamarthi 2025)
  - We are the largest quasi-experimental study (17 years, 18 million deaths)
  - We focus on mortality dynamics

Background and Data

Daily environmental data

- Air pollution: EPA site monitors
  - Not available for all counties $\rightarrow$ limiting factor in the final size of our sample

- Wind direction and wind speed: ERA5 reanalysis dataset

- Temperature and precipitation: Schlenker and Roberts (2009)

- Relative humidity: NOAA Physical Sciences Laboratory

- We aggregate all data to the **county-day level**

Daily mortality data

- National Vital Statistics, 1972–1988
  - Exact date of death
  - County of occurrence
  - Age and cause of death

- Merge with environmental data at the county-day level
  - Main specification includes 2.04 million county-day observations

Summary statistics

	(1)	(2)	(3)
	Mean	Std. Dev.	Observations
A. Pollution outcomes			
SO_2, ppb	9.07	12.68	2,042,258
NO_2, ppb	21.45	15.74	796,539
CO, ppm	1.67	1.40	855,824
O_3, ppb	25.54	13.73	674,340
TSP, μg/m^3	63.23	40.10	634,095
B. One-day mortality rate outcomes			
All-cause mortality, deaths per million	24.33	22.88	2,042,258
Cardiovascular	12.03	15.47	2,042,258
Cancer	5.08	8.97	2,042,258
Other	5.36	9.78	2,042,258
External	1.86	7.94	2,042,258

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Empirical Analysis

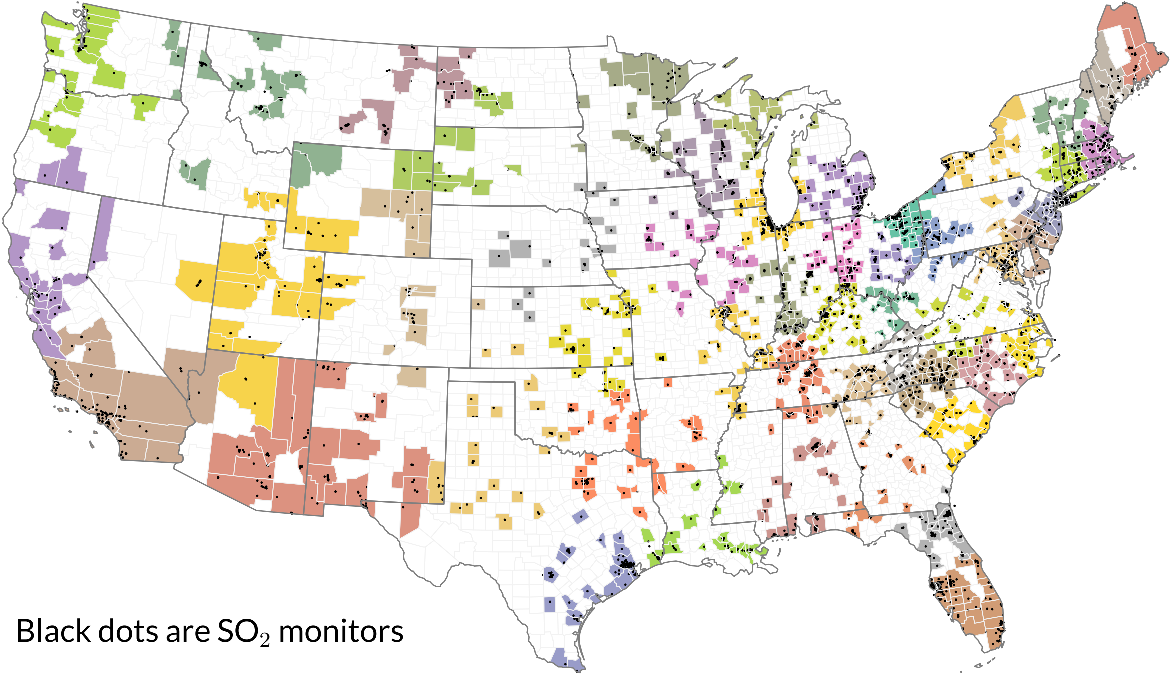
Short-run effects of acute exposure

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

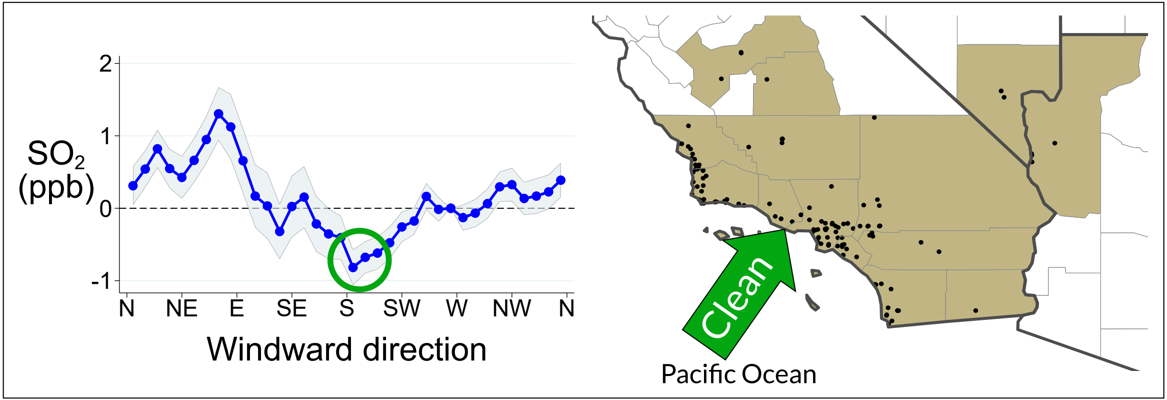
How do we construct our instruments?

- 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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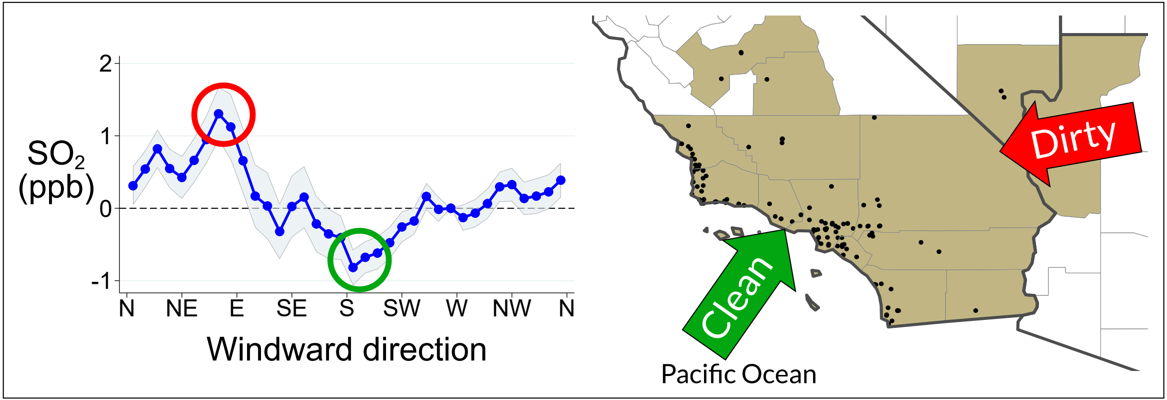

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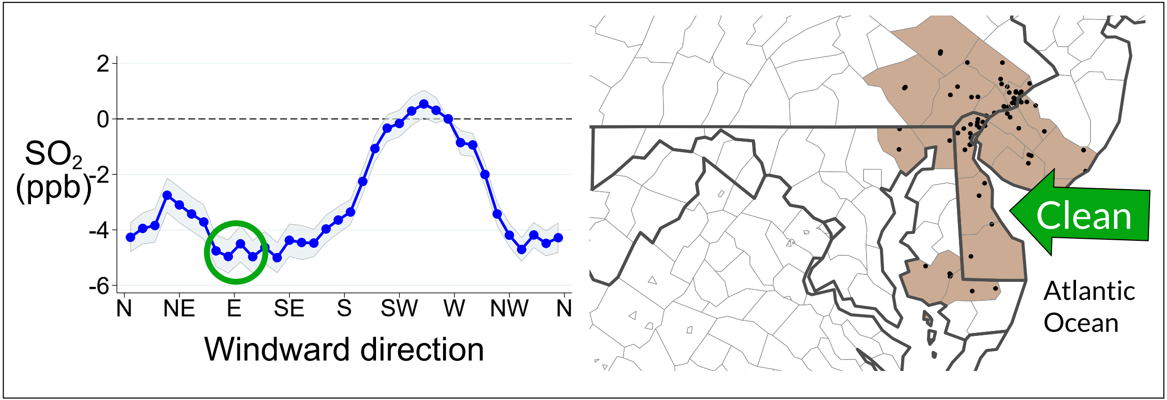
Wind direction and SO_2 in Greater Philadelphia area



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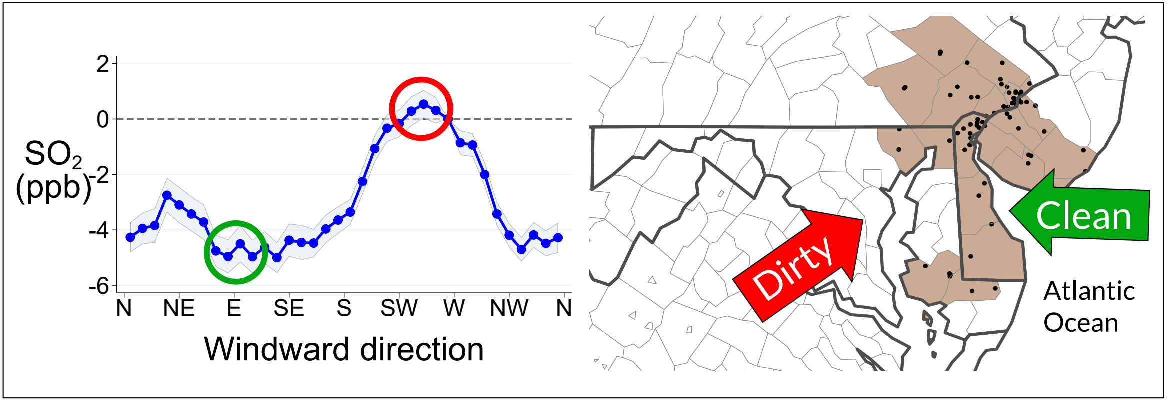

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First stage: excluded instrument is wind direction

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

- 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 $f^g(\theta_{cd})$
  - Non-parametric 40-degree bins (400 instruments)
  - Parametric sin function (100 instruments, preferred specification) ▸ Example

Second-stage regression

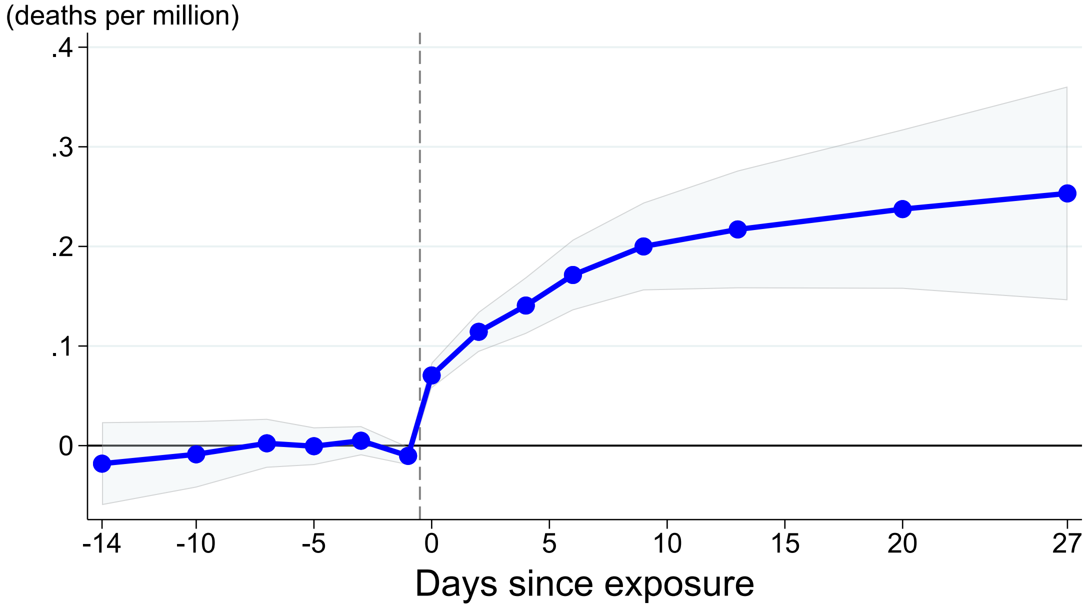
$$Y_{cd}^{k} = \beta^{k}\widehat{\mathsf{SO2}}_{cd} + X_{cd}^{k}{}'\delta + \alpha_{cm} + \alpha_{my} + \varepsilon_{cd}$$

- Estimate effect of 1-day exposure on k-day mortality rate (up to $k = 90$)

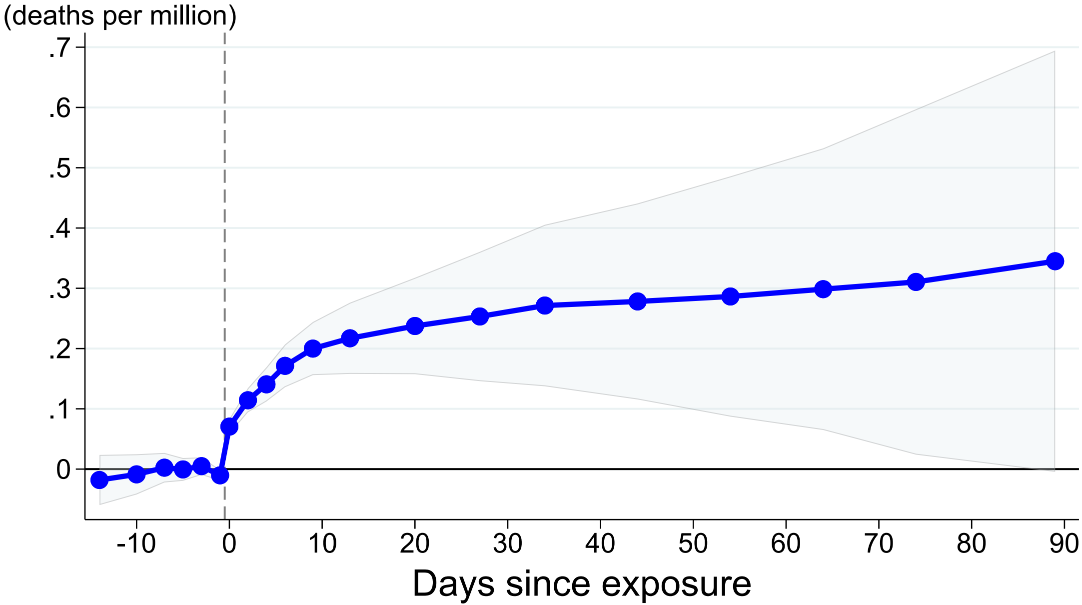
- Controls include:
  - county×calendar-month (α_{cm}) and calendar-month×year (α_{my}) fixed effects
  - flexible function of temperature, precipitation, humidity, and wind speed
  - $k - 1$ leads of weather controls, and 2 lags/leads of the instruments

- Cluster standard errors at the county level, weight by county population

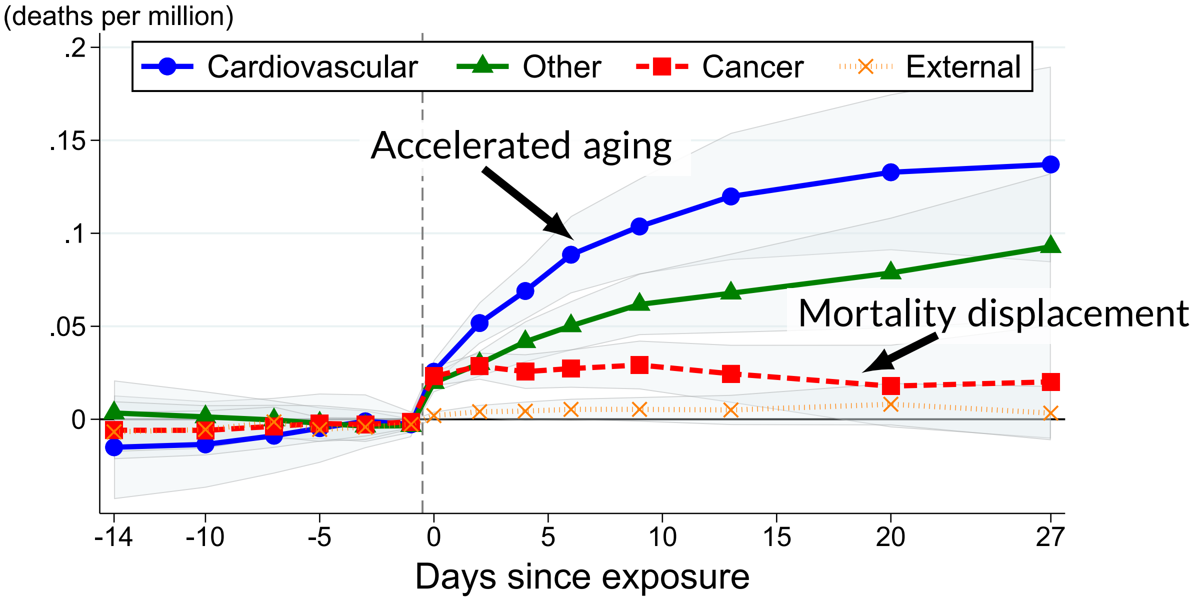
Growing cumulative mortality effect (28 days)



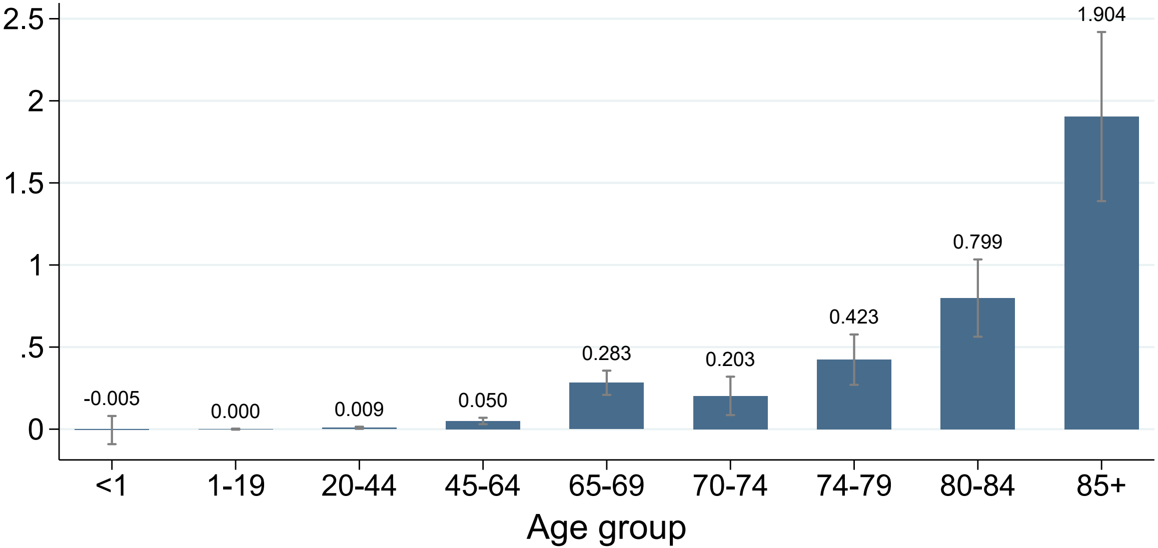
Growing cumulative mortality effect (90 days)



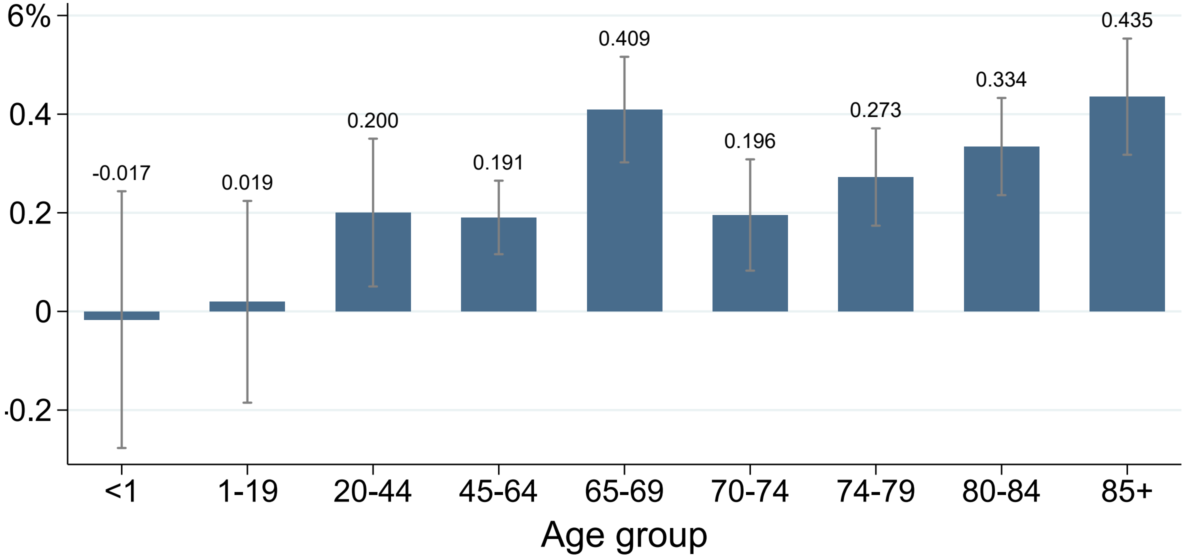
Divergent patterns by cause of death



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
- Placebo test: random wind direction produces weak first stage ($F < 4$) ▸ Table
- Geographic compliers analysis ▸ Figure

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)

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

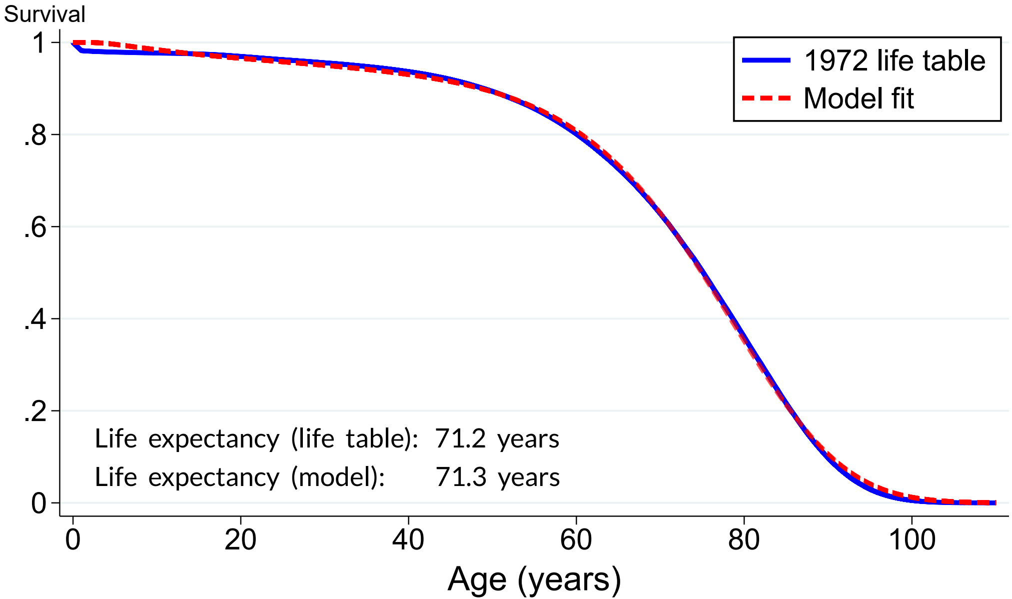
- Death occurs when health capital falls below threshold $\underline{\mathsf{H}} = 0$:

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

- 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

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

Exposure affects mortality through two channels:

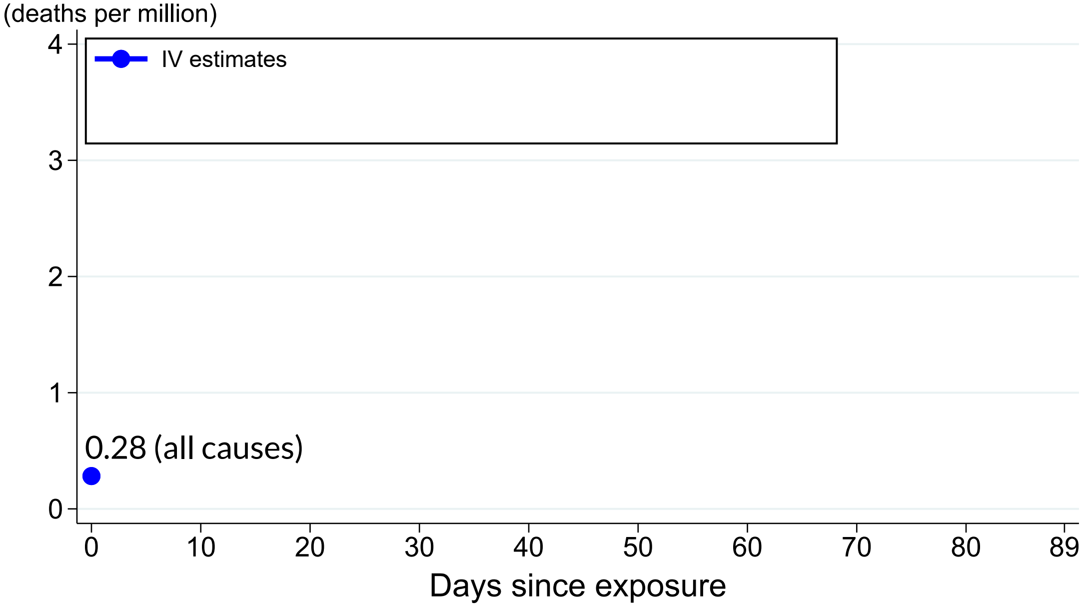
1. Depreciation: $\delta \rightarrow \widetilde{\delta}$
   - accelerated aging effect
   - calibrate using 1-day non-cancer IV estimate
2. Death threshold: $\underline{\mathrm{H}} \rightarrow \widetilde{\underline{\mathrm{H}}}$
   - mortality displacement
   - calibrate using 1-day cancer IV estimate

Example: ages 65–69

	(1)	(2)
Age group	All causes	Cancer-related causes
65–69	0.28**	0.13**
	(0.038)	(0.021)
70–74	0.20**	0.12**
	(0.060)	(0.025)
75–79	0.42**	0.14**
	(0.078)	(0.034)
80–84	0.80**	0.12*
	(0.12)	(0.053)
85+	1.9**	0.16**
	(0.26)	(0.060)

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

Example: ages 65–69



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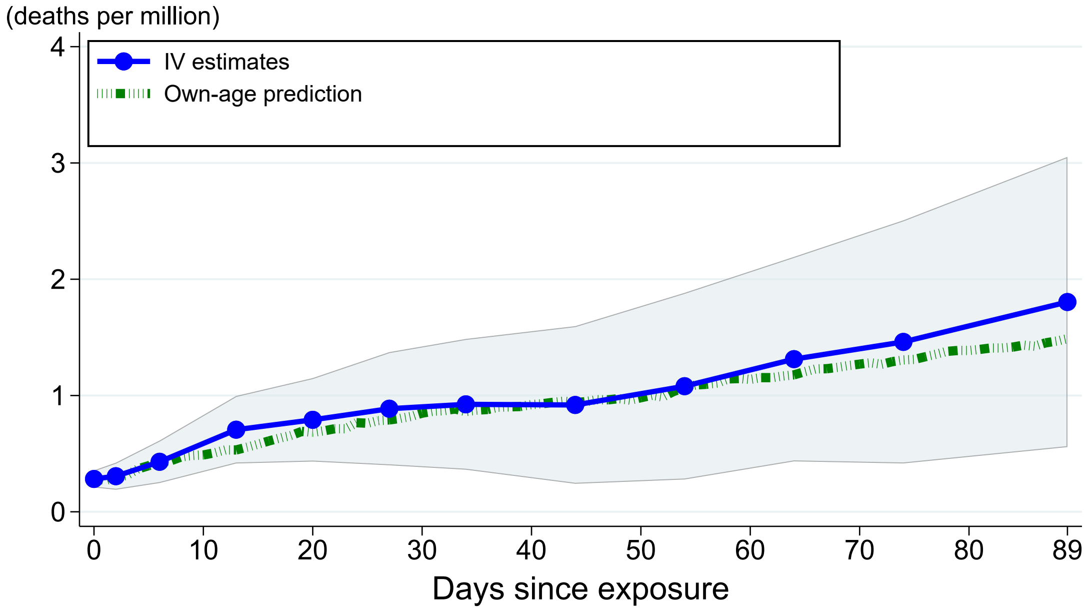

“Leave-one-out” validation: calibrate using other ages

	(1)	(2)
Age group	All causes	Cancer-related causes
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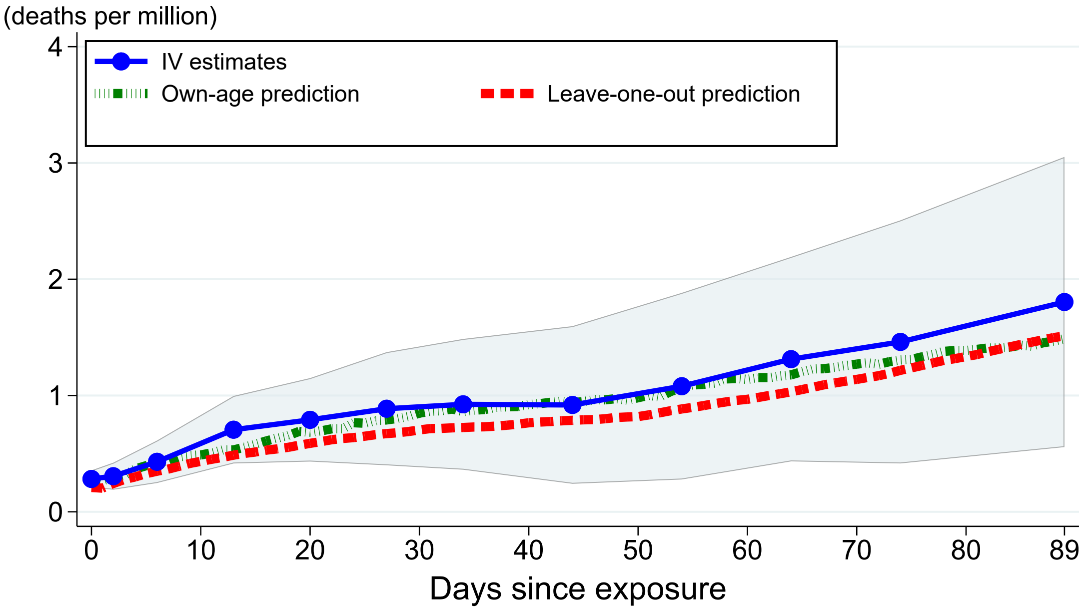

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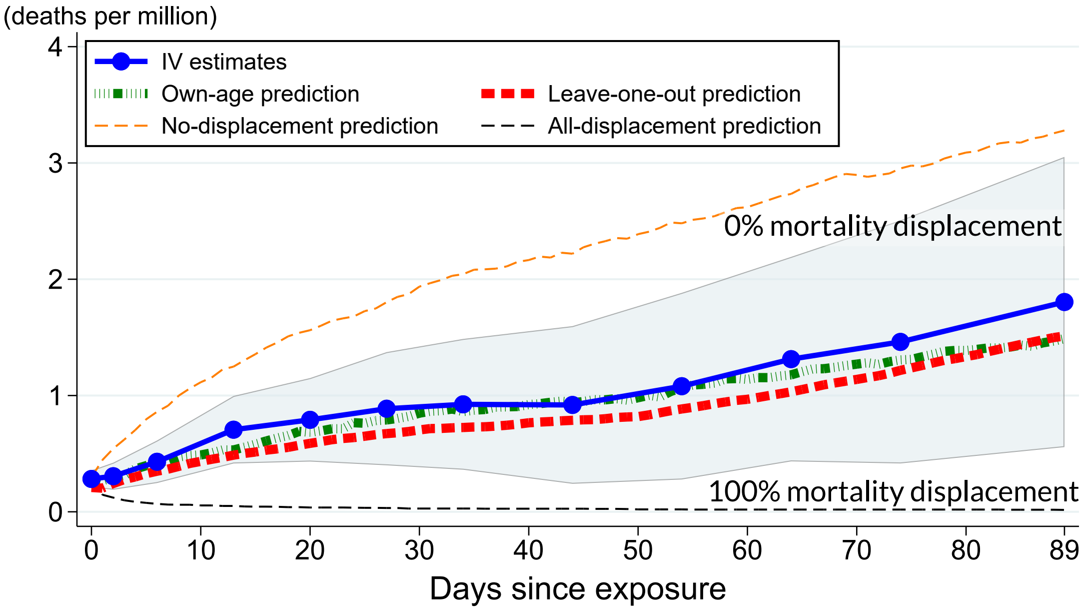
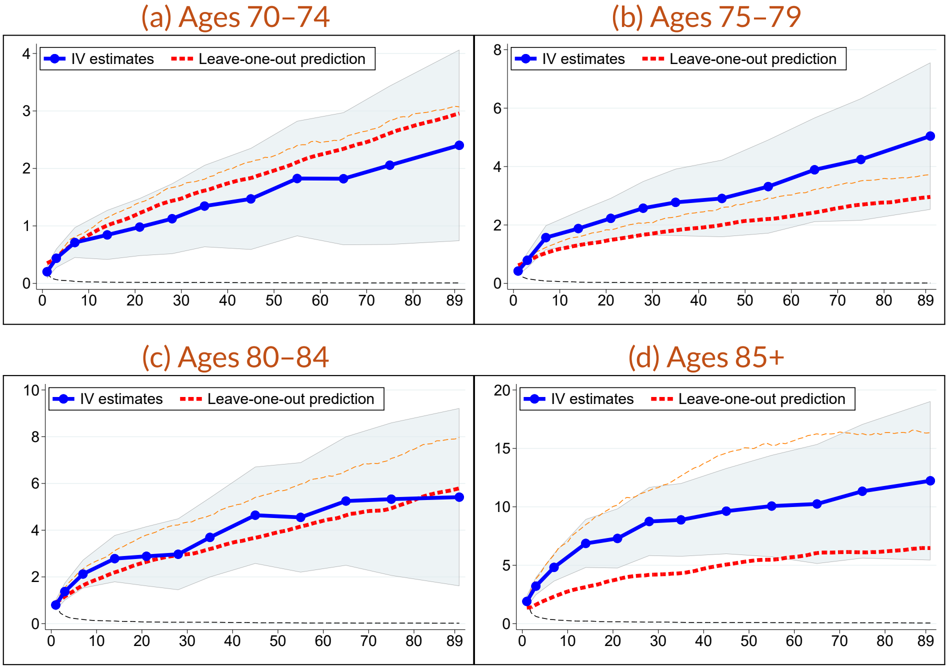



(a) Ages 70–74
IV estimates
Leave-one-out prediction
0
1
2
3
4
0
10
20
30
40
50
60
70
80
89
(b) Ages 75–79
IV estimates
Leave-one-out prediction
0
2
4
6
8
0
10
20
30
40
50
60
70
80
89
(c) Ages 80–84
IV estimates
Leave-one-out prediction
0
2
4
6
8
10
0
10
20
30
40
50
60
70
80
89
(d) Ages 85+
IV estimates
Leave-one-out prediction
0
5
10
15
20
0
10
20
30
40
50
60
70
80
89

Validation: prolonged exposure

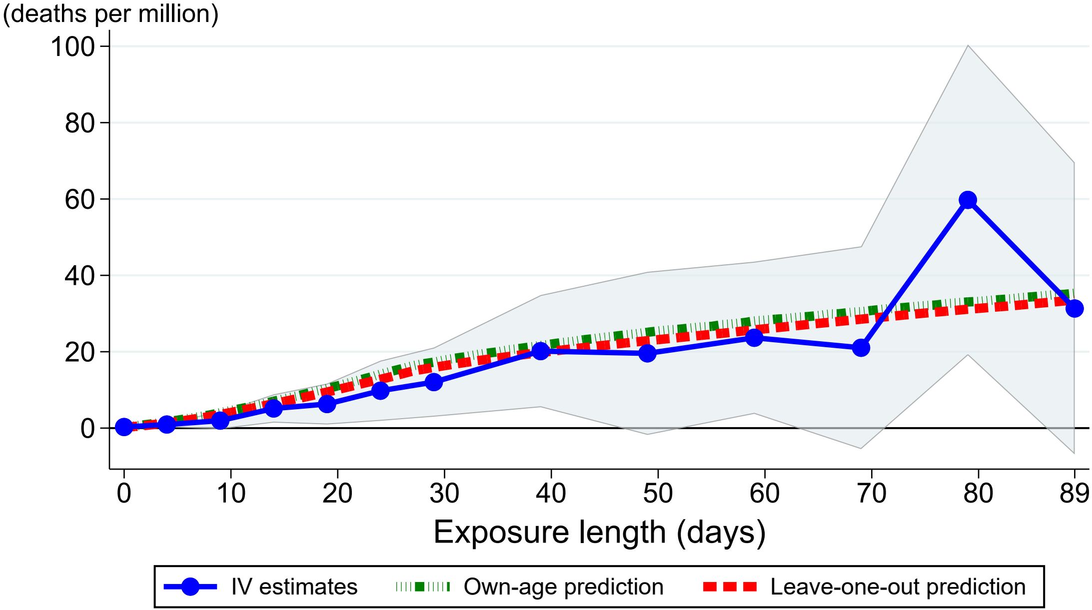
- Use first-stage estimates to predict wind-driven daily SO_2 concentrations:

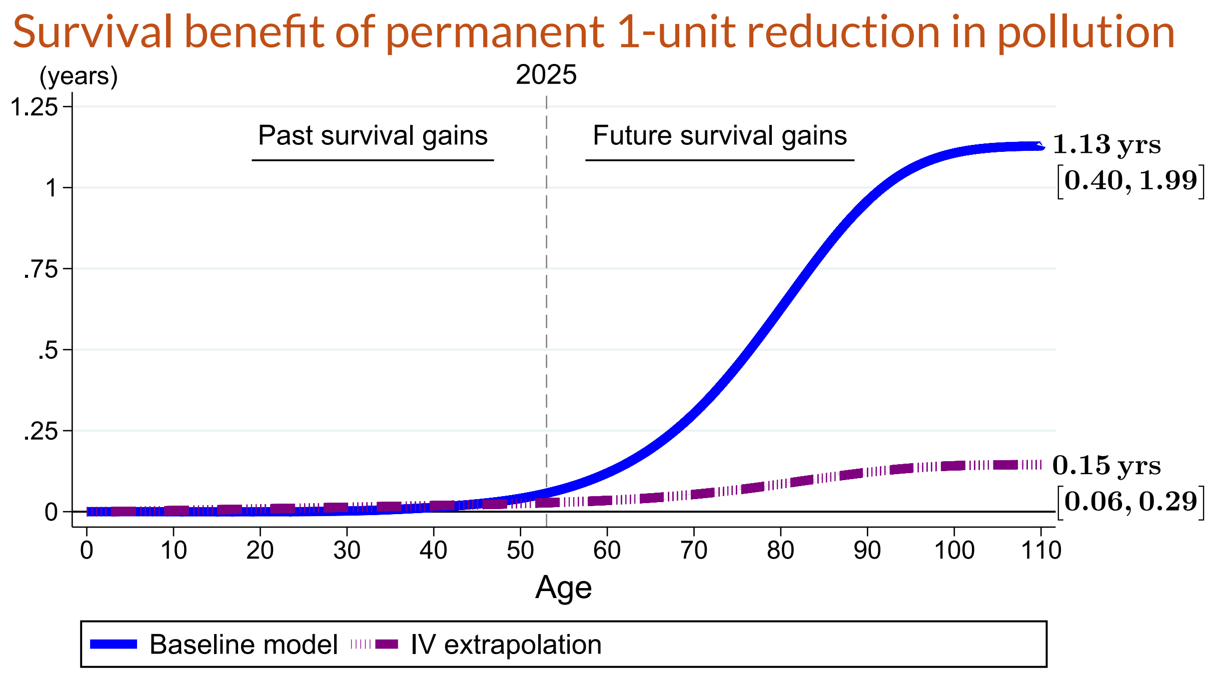
$$\widehat{\mathsf{SO2}}_{cd} = \sum_{g=1}^{50} \widehat{f}^{g}(\theta_{cd})$$

- Aggregate into multi-day periods ranging from 2 to 90 days

- Estimate aggregated regressions using aggregated predictions as instrument

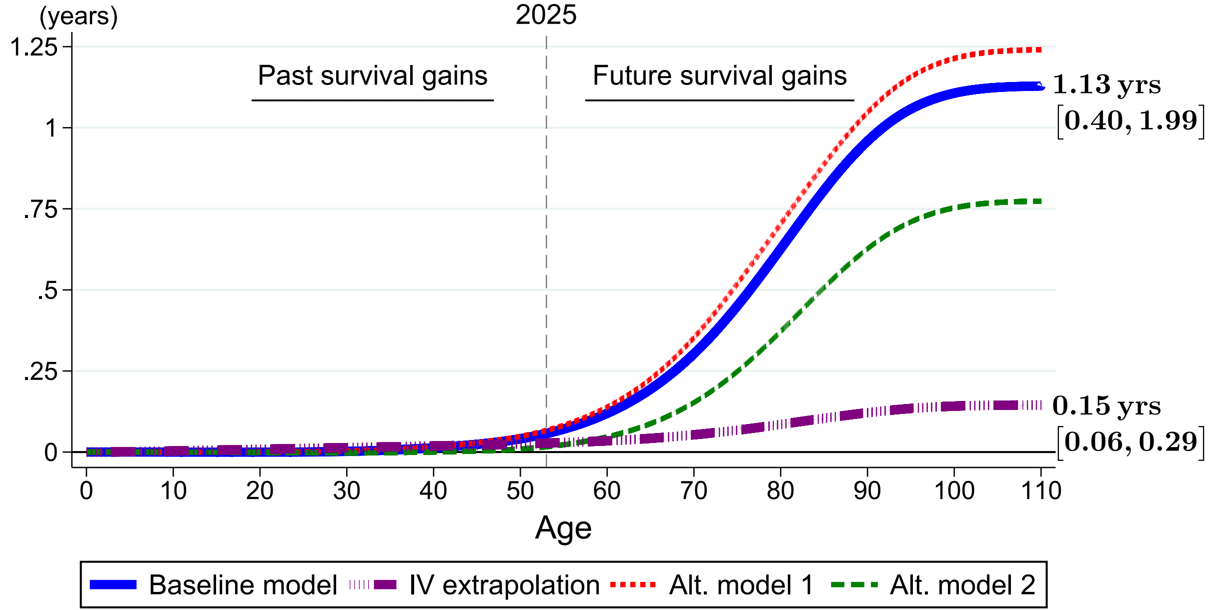
Validation: prolonged exposure estimates (ages 65–69)





Survival benefit of permanent 1-unit reduction in pollution
(years)
2025
1.25
1
.75
.5
.25
0
Past survival gains
Future survival gains
1.13 yrs
[0.40, 1.99]
0.15 yrs
[0.06, 0.29]
0
10
20
30
40
50
60
70
80
90
100
110
Age
Baseline model
IV extrapolation

Survival benefit of permanent 1-unit reduction in pollution

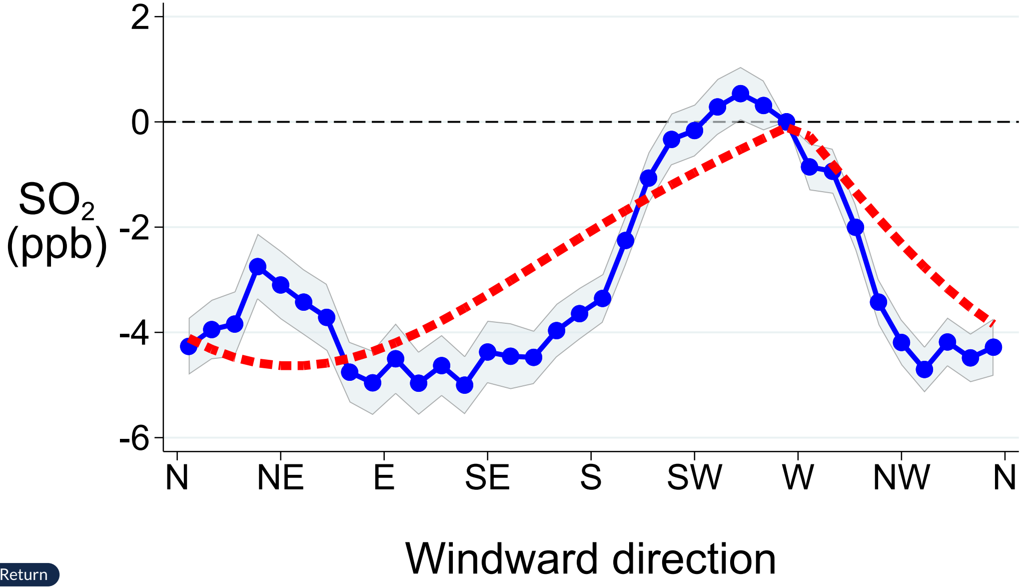


Conclusion

- Air pollution causes mortality displacement and accelerating aging
- Permanent, 10% reduction in exposure improves life expectancy by 1.1 yrs
  - 7 times larger than naive 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)	(5)
SO_2, ppb	0.070**	0.074**	0.067**	0.068**	0.069**
	(0.0065)	(0.0063)	(0.0065)	(0.0065)	(0.0063)
First-stage *F*-statistic	636	669	626	635	637
Mean outcome	24	24	24	24	24
Sample size	2,042,258	2,042,258	2,040,691	2,041,828	2,037,216
Number of weather controls	2,373	0	10,150	3,954	16,152
Weather controls					
Baseline weather variables	X		X	X	X
Min. temperature variables			X	X	
Less granular bins				X	
Grid-level 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)
SO_2, ppb	0.089**	0.053**	0.068**	0.053**
	(0.014)	(0.017)	(0.017)	(0.018)
TSP, μg/m^3		0.021**		0.021**
		(0.0056)		(0.0047)
NO_2, ppb			0.046*	0.015
			(0.018)	(0.018)
O_3, ppb			–0.045	–0.057**
			(0.029)	(0.021)
CO, ppm			–0.084	–0.059
			(0.25)	(0.19)
First-stage *F*-statistic	91	20	12	10
Mean outcome	27	27	27	27
Sample size	79,049	79,049	79,049	79,049

Notes: The dependent variable is number of deaths per million people on the day of exposure.

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

	(1)	(2)	(3)
SO_2, ppb	0.063**		0.030*
	(0.0077)		(0.012)
TSP, $\mu g/m^3$		0.027**	0.017**
		(0.0040)	(0.0059)
First-stage *F*-statistic	243	117	46
Mean outcome	25	25	25
Sample size	633,878	633,878	633,878

Notes: The dependent variable is number of deaths per million people on the day of exposure. A */** indicates significance at the 5%/1% level.

Return

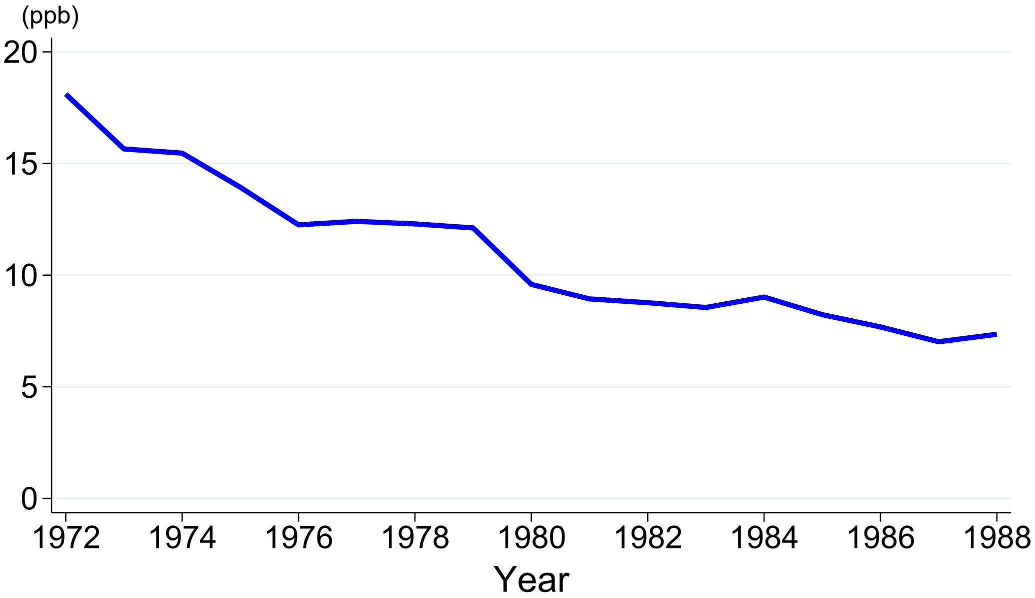
Placebo tests using randomly generated wind directions

	(1)	(2)	(3)
SO_2, ppb	0.027	−0.32	−0.51
	(0.060)	(0.22)	(0.50)
Outcome window, days	1	7	28
First-stage *F*-statistic	3.3	3.5	3.7
Mean outcome	24	170	681
Sample size	2,042,258	2,042,258	2,042,258

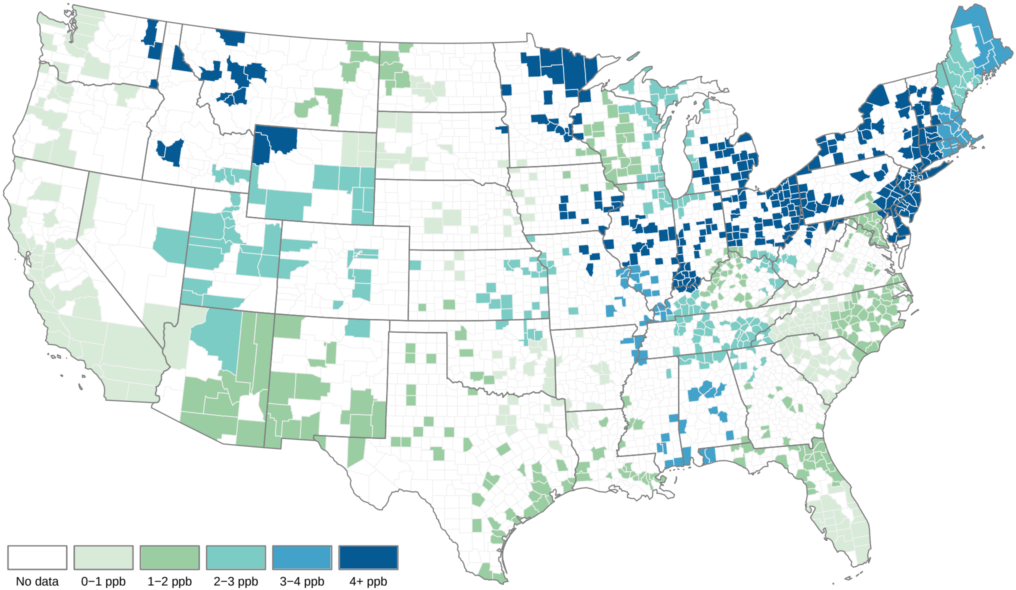
Notes: The dependent variable is cumulative number of deaths per million people in the days following acute (1-day) exposure. A */** indicates significance at the 5%/1% level.

◂ Return

SO_2 levels are declining during our sample period



Strength of the first stage, by geographic group



Return

Effect of permanent change in SO_2 on survival gains (years)

	(1)	(2)	(3)	(4)
	IV extrapolation	Baseline model	Alt. model 1	Alt. model 2
1-ppb decrease	0.15	1.13	1.24	0.77
	[0.06, 0.29]	[0.40, 1.99]	[0.70, 1.98]	[0.04, 1.63]
2-ppb decrease	0.29	2.32	2.28	1.58
	[0.11, 0.58]	[0.70, 4.10]	[1.55, 3.03]	[–0.04, 3.35]
3-ppb decrease	0.44	3.45	3.40	2.36
	[0.17, 0.88]	[0.99, 6.26]	[2.35, 4.77]	[–0.09, 5.17]

Notes: In the absence of any change in exposure, predicted life expectancy is 71.3 years. 90% bootstrap confidence intervals are reported in brackets.