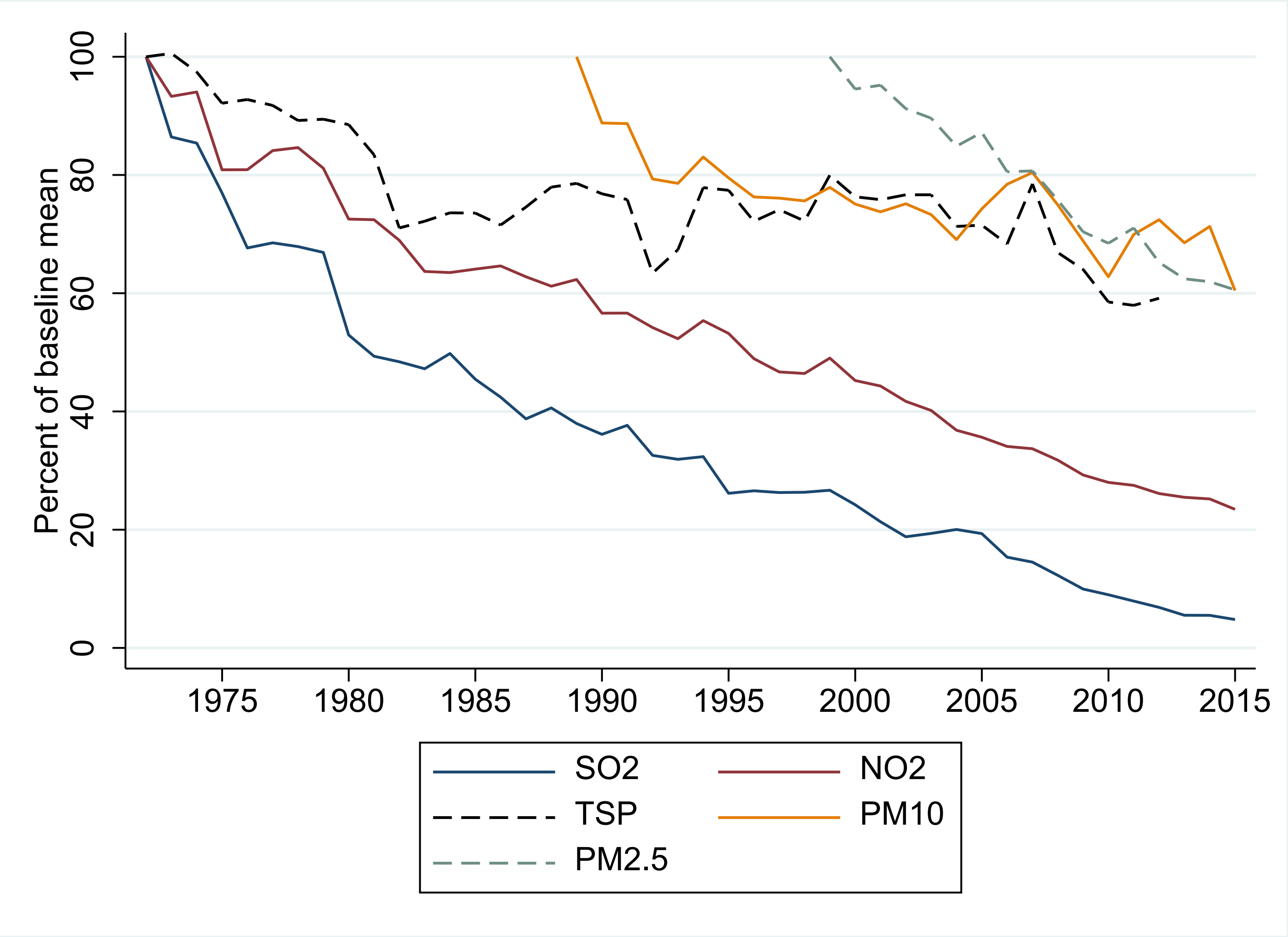
How many lives are saved by reductions in fossil fuel use?

Tatyana Deryugina

Fossil fuel, climate change, and air pollution

- Drastically reducing fossil fuel emissions of greenhouse gases is necessary for combatting climate change
- Reducing fossil fuel use also reduces emissions of air pollutants that affect human health, creating so-called “co-benefits” of climate change policy
- Magnitude of co-benefits depends on how harmful air pollution is to human health (and for other outcomes)
  - What is the magnitude of this harm, especially in places where air pollution levels are already low?

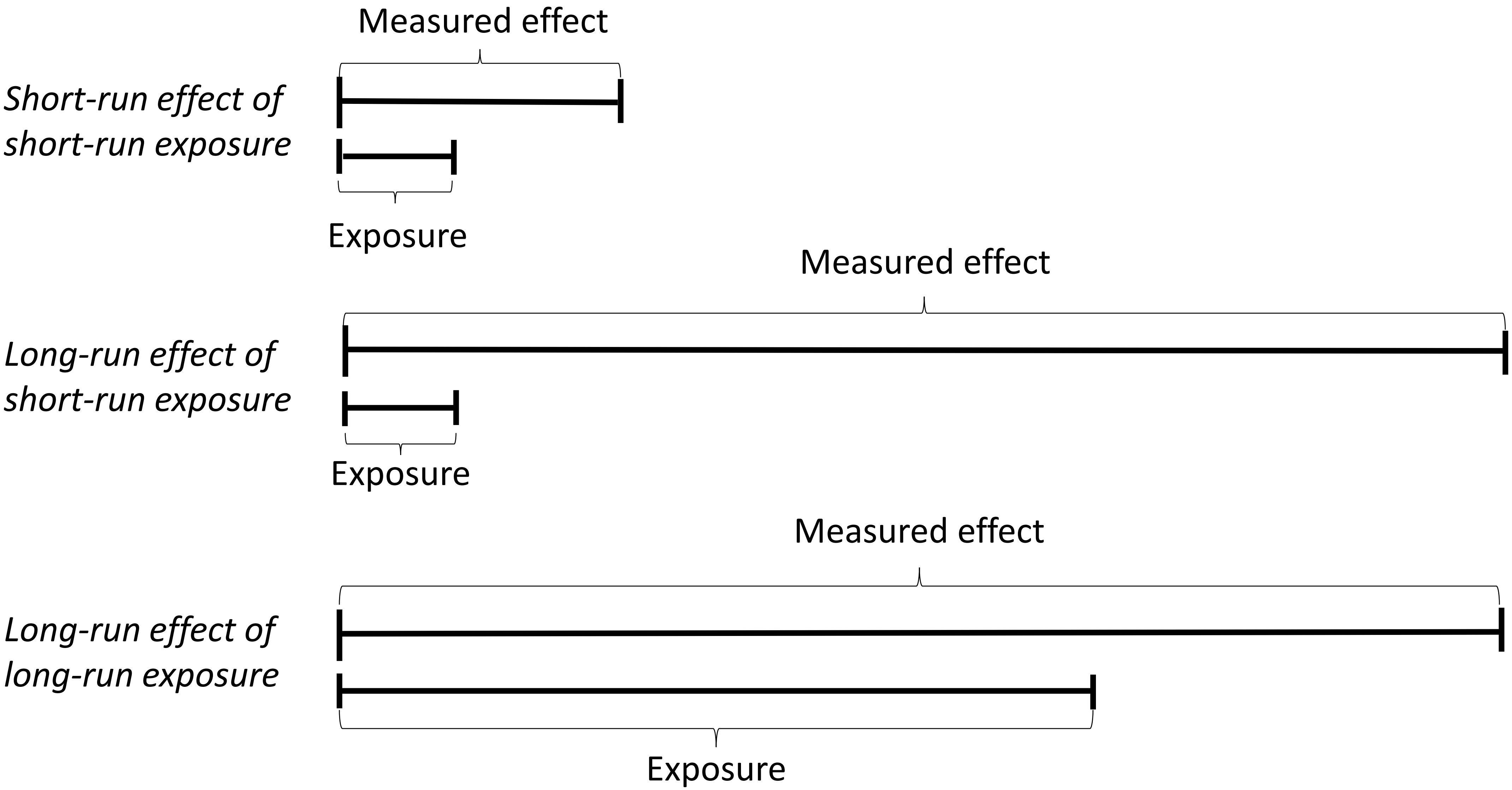
Air pollution levels in rich countries have fallen dramatically in the past 50 years



Quantifying the health costs of air pollution is difficult

1. Air pollution not as good as randomly assigned
2. Ambient air pollution levels are measured with error
3. Air pollution may have delayed health effects
4. Increases in air pollution may kill individuals who would have died "soon" regardless of the shock ("mortality displacement")
5. Individuals may take defensive actions (e.g., medication, relocation) to counteract negative health effects

What are we measuring? A taxonomy

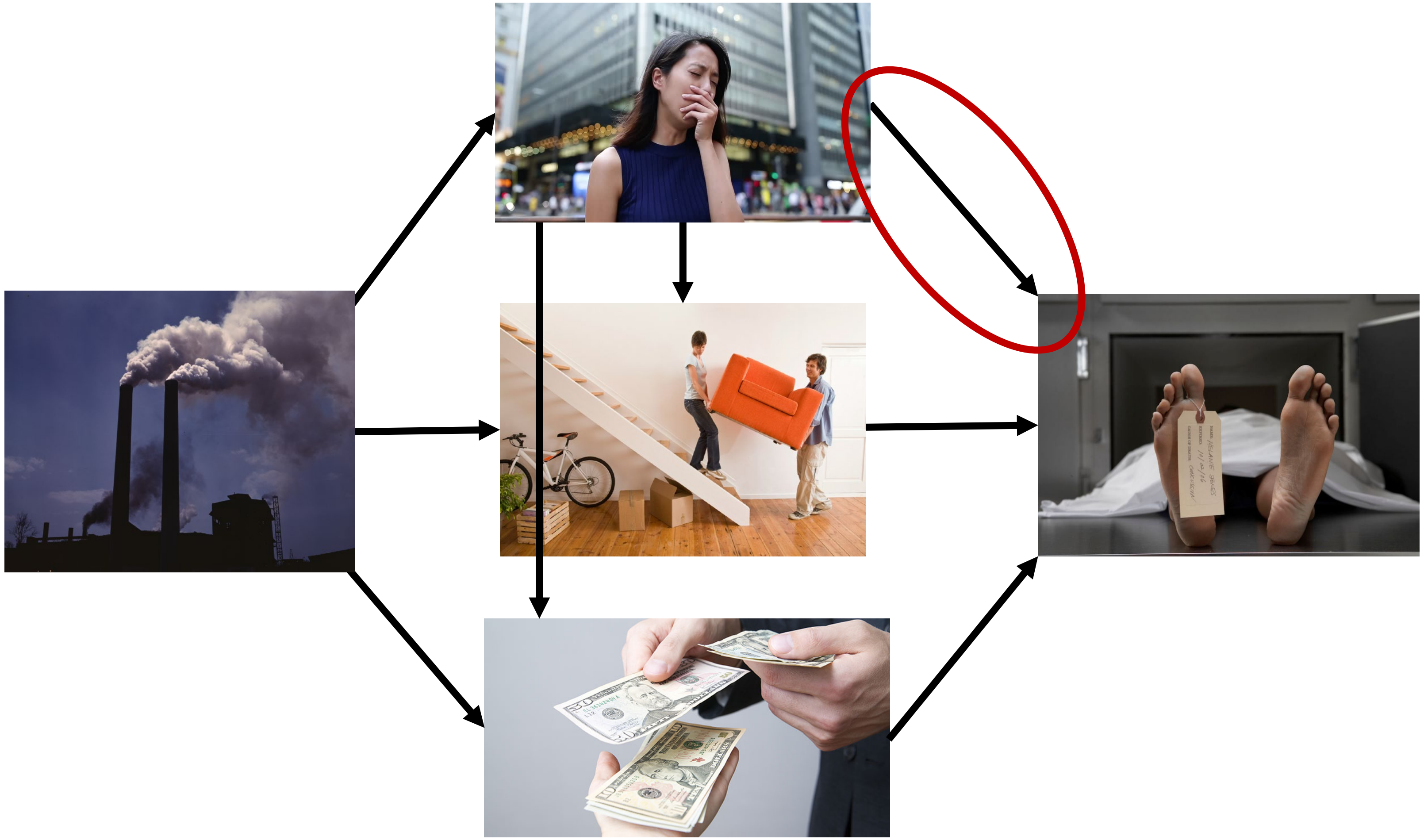


The best-identified studies focus on outcomes over short-ish time frames

- <u>Infants</u>:
  - EZ pass introduction and birth weight/prematurity (Currie & Walker 2011)
  - Traffic congestion and weekly infant mortality (Knittel et al. 2016)
- <u>Adults</u>:
  - CO and daily hospitalizations (Schlenker & Walker 2016)
  - $PM_{2.5}$ and mortality/hospitalizations over 1-28 days (Deryugina et al. 2019)
  - Excess emissions and monthly mortality (Hollingsworth et al. 2021)
  - $PM_{2.5}$ and healthcare spending over 1-90 days (Barwick et al. 2021)
  - Leaded gasoline and annual mortality (Hollingsworth & Rudik 2021)
  - NO_X and annual healthcare spending/hospitalizations/mortality (Deschenes et al. 2017)

Measuring outcomes over longer time periods creates other issues

- Barreca et al (2021): larger cross-sectional mortality decreases in counties that experienced larger reductions in SO_2 as a result of the Acid Rain Program



Assessing counterfactual survival of those killed by air pollution

- Option 1: consider mortality impacts over different time windows following air pollution shocks
  - As $T \rightarrow \infty$, effect of air pollution on mortality over time period T goes to zero
  - Empirically measuring the time period T over which the effect of pollution on mortality disappears informs counterfactual survival of those affected
  - But statistical power may quickly become an issue

- Option 2: use data to model counterfactual survival
  - Not limited by length of follow-up window
  - Data intensive and requires some assumptions

Elderly killed by acute air pollution exposure have substantially lower counterfactual survival than typical elderly

		Life-years lost regressions				
	(1) All-age mortality	(2) None	(3) Age, sex	(4) Age, sex, chronic conditions	(5) Survival random forest	(6) Cox-Lasso
PM 2.5 ($\mu g/m^3$)	0.850 (0.079)	9.657 (0.893)	6.509 (0.700)	3.901 (0.520)	3.048 (0.542)	2.991 (0.487)
F-statistic	304	304	304	304	304	304
Dep. var. mean	459	5,208	3,556	2,398	2,401	2,224
Effect relative to mean, percent	0.185	0.185	0.183	0.163	0.127	0.134
LYL per decedent	NA	11.357	7.755	5.230	5.236	4.850
LYL per complier	NA	11.357	7.655	4.587	3.585	3.517
Observations	1,898,236	1,898,236	1,898,236	1,898,236	1,898,236	1,898,236

Source: Deryugina, Heutel, Miller, Molitor, and Reif (2019)

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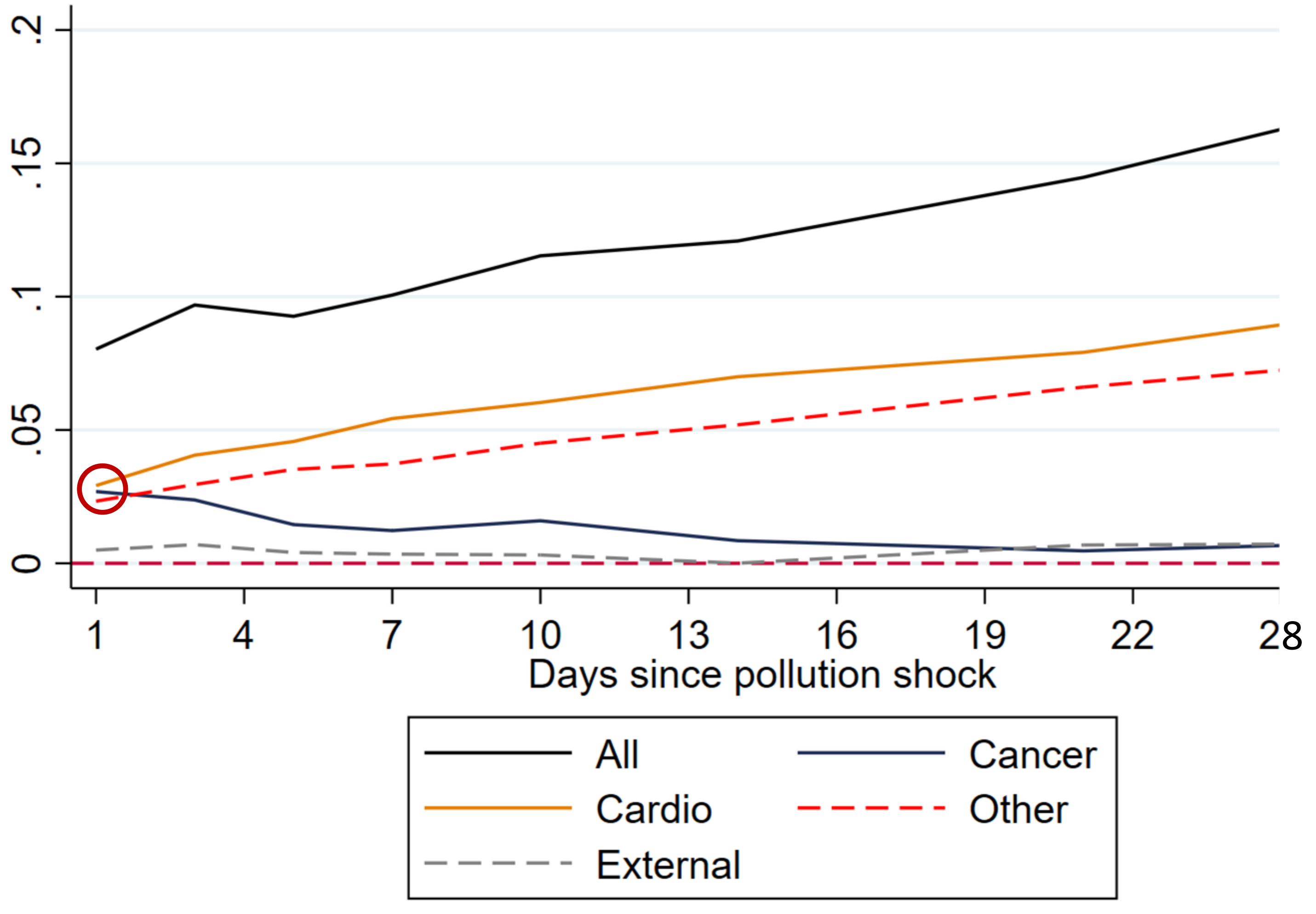
Air pollution shocks have delayed effects *and* create short-run mortality displacement

- Exogenous change: 1-day 1-unit increase in sulfur dioxide (SO_2)
  - Instruments: daily changes in wind direction, controlling for a host of fixed effects and other weather conditions
- Dependent variables: county-level X-day (cumulative) mortality rate from specific cause
  - Sample: US counties with SO_2 monitors in 1972-1988



Source: Deryugina and Reif (2022)

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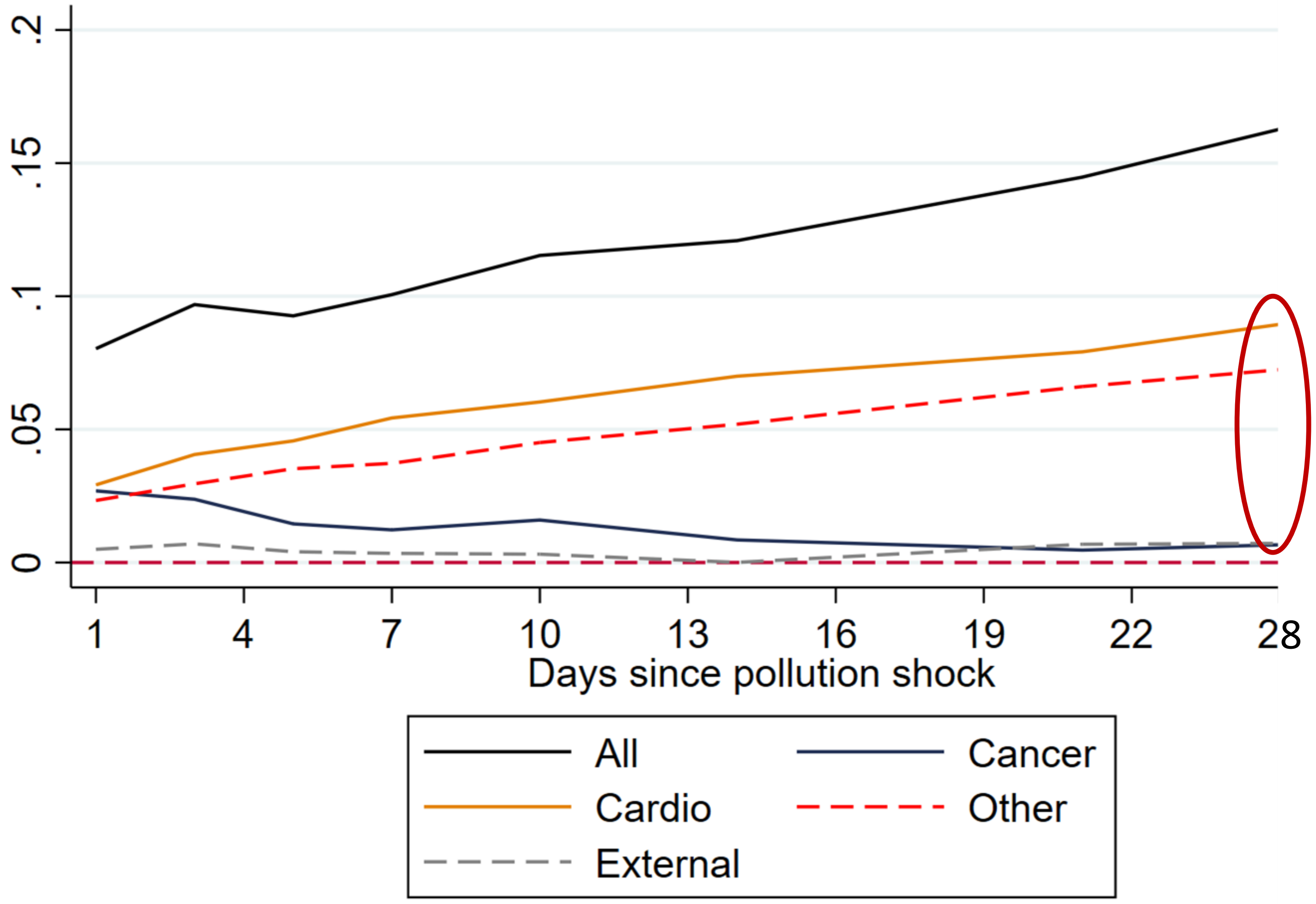


Source: Deryugina and Reif (2022)

Leveraging structural models for enhanced understanding of impacts

- Estimating long-run effects of air pollution using quasi-experimental methods has proven difficult

- Economists don’t have a good answer to “How much has life expectancy in the US improved as a result of pollution declines?”

- Proposed complementary approach: use well-identified shorter-run estimates to calibrate a dynamic model of health capable of predicting longer-run impacts

Model: Lleras-Muney and Moreau (2022)

$$\underbrace{H_t}_{\text{health capital at time } t} = H_{t-1} - \underbrace{d(t)}_{\substack{\text{depreciation} \\ \delta t^{\alpha}}} + \underbrace{I}_{\text{Investment}} + \underbrace{\epsilon_t}_{\substack{\text{iid health shock} \\ \sim N(0,\sigma_\epsilon^2)}}$$

$H_0 \sim N(\mu_H, 1)$: initial health stock

Model depends on 5 parameters: $\mu_H, \delta, \alpha, I, \sigma_\epsilon^2$

Model: Lleras-Muney and Moreau (2022)

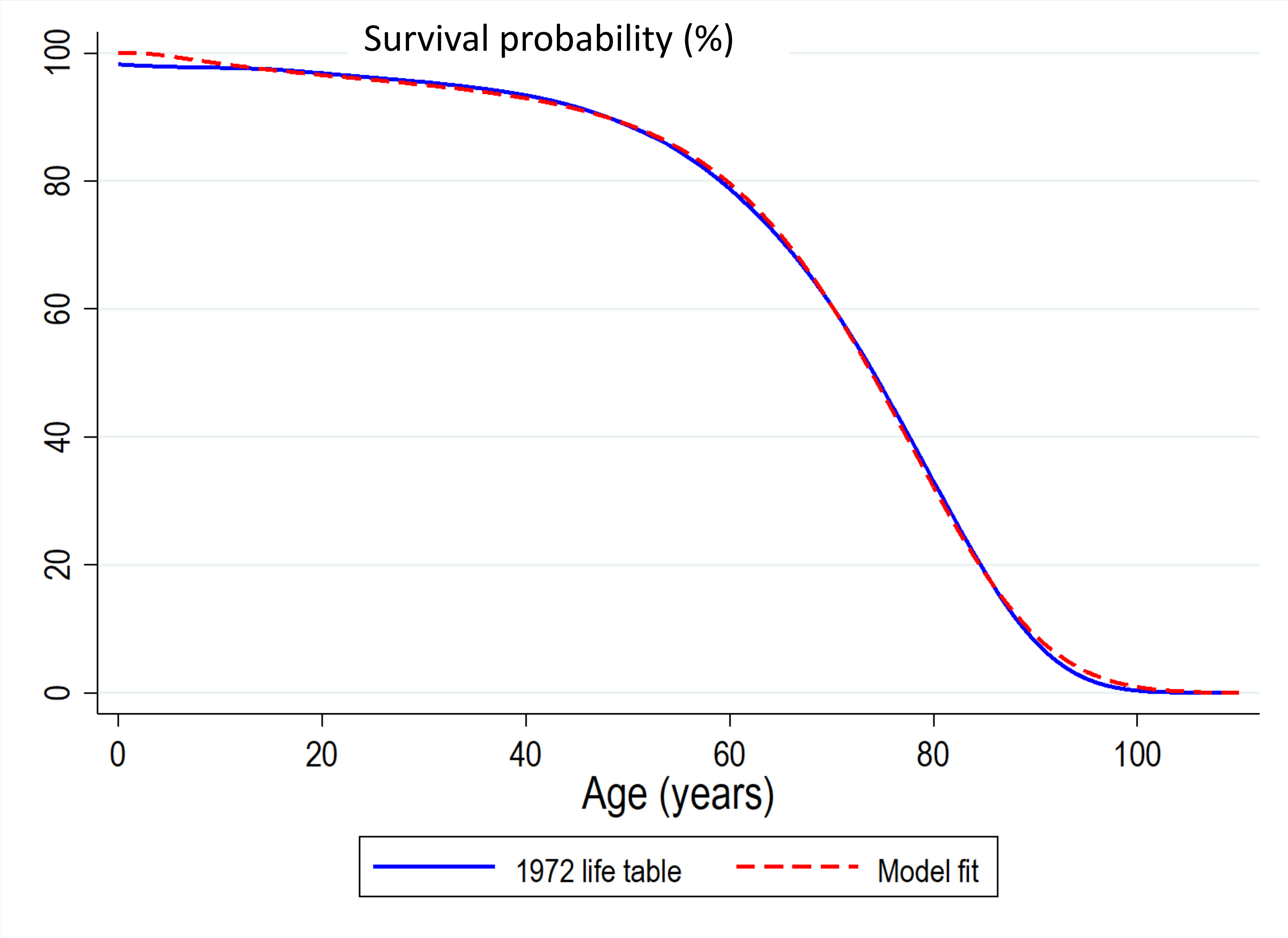
$$H_t = H_{t-1} - d(t) + I + \epsilon_t$$

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

$$D_t = 1\left[H_t < \underline{H}, D_{t-1} = 0\right]$$

- Model captures a variety of real-world mortality dynamics
  - “Rectangularization” of survival
  - Socioeconomic gradients
  - “Scarring” effects
  - Mortality displacement

Calibrate the model using a period life table



N = 1,000,000 agents

<u>Calibrated parameters</u>:

μ_H = 10.6

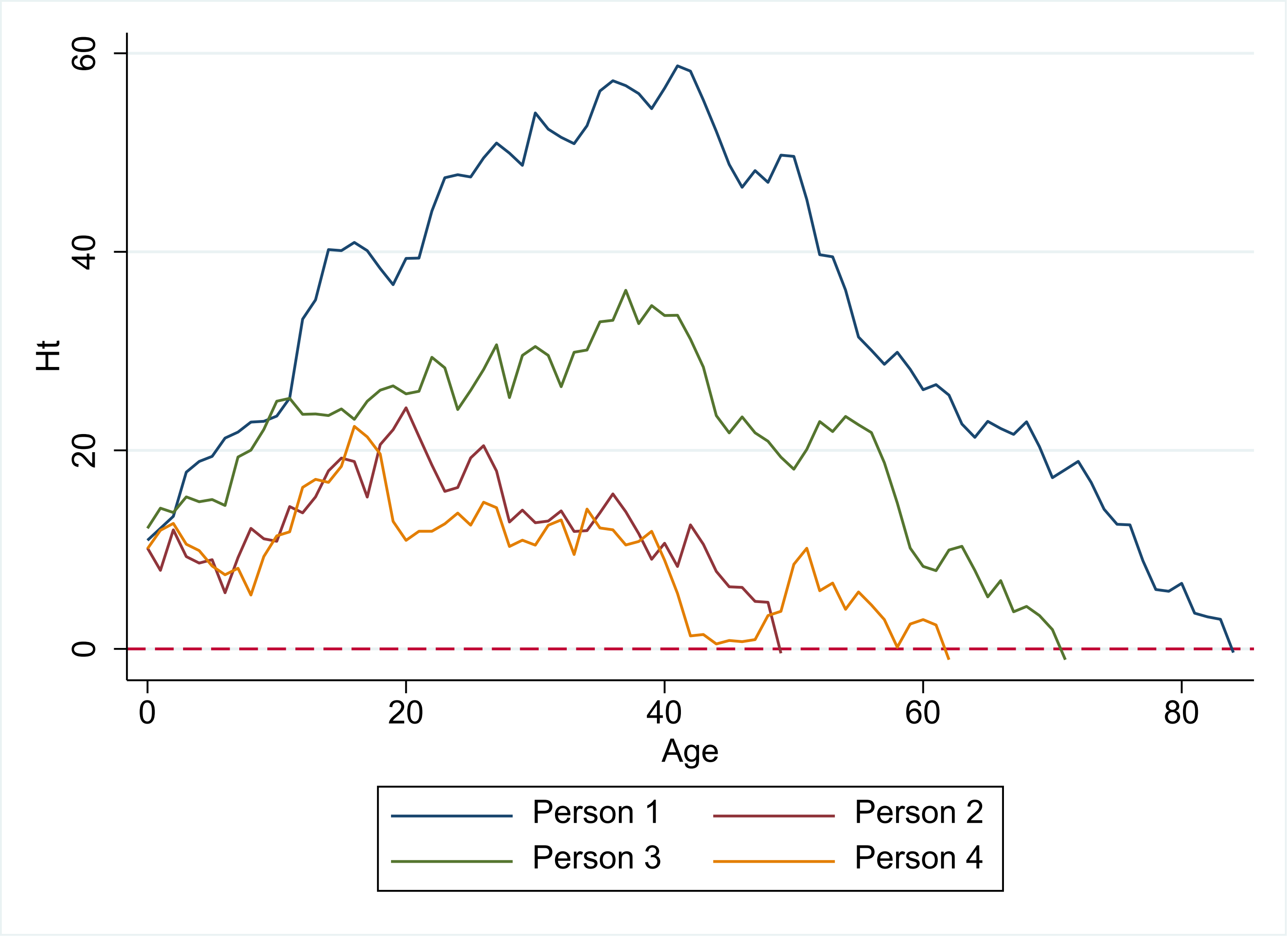
δ = 0.00354

α = 1.51

I = 0.813

σ_e = 2.37

Example health trajectories



$$H_t = H_{t-1} - d(t) + I + \epsilon_t$$

Estimating change in model parameters

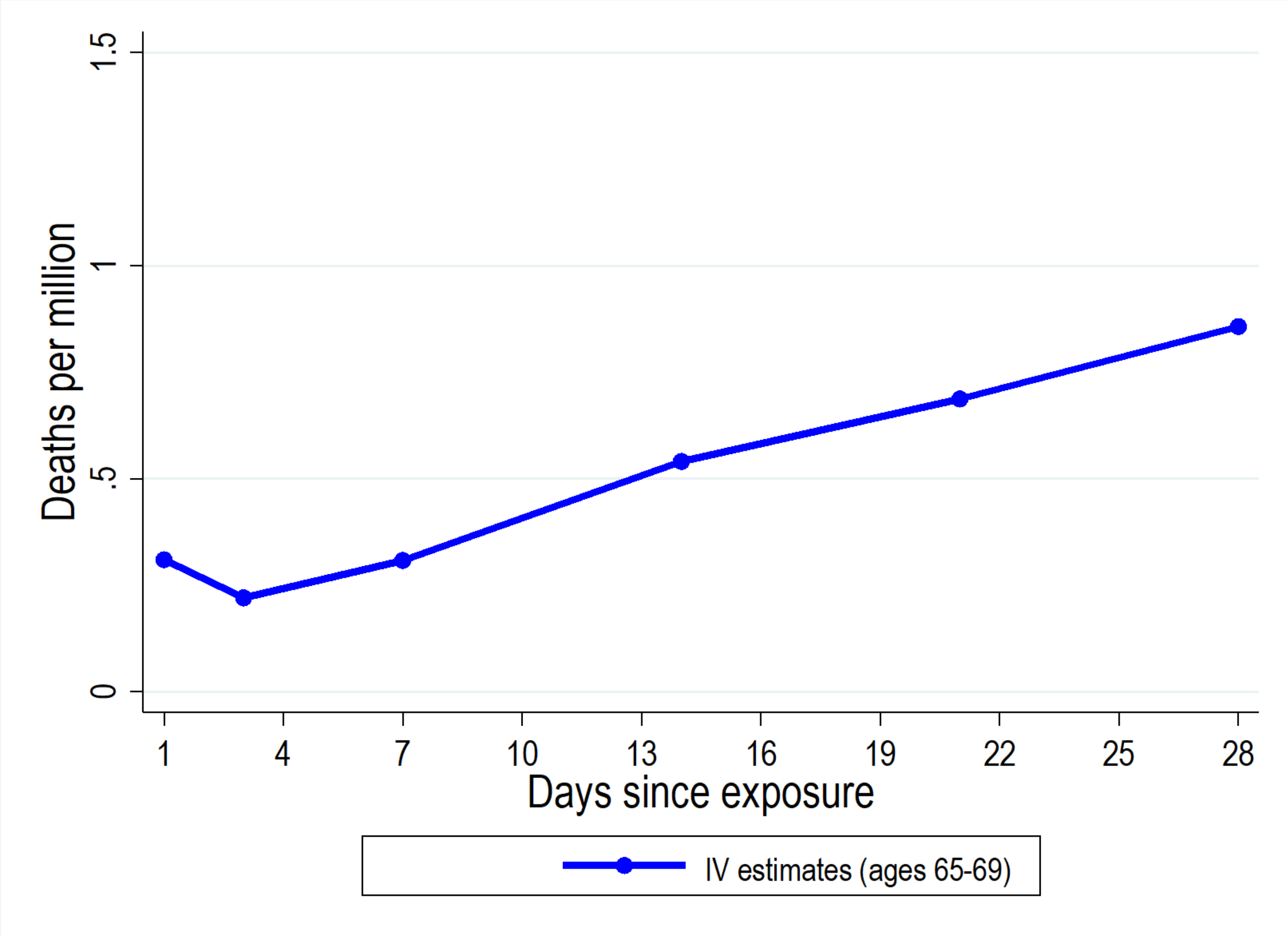
$$H_t = H_{t-1} - d(t) + I + \epsilon_t$$

$$D_t = 1\left[H_t < \underline{H}, D_{t-1} = 0\right] \; (death)$$

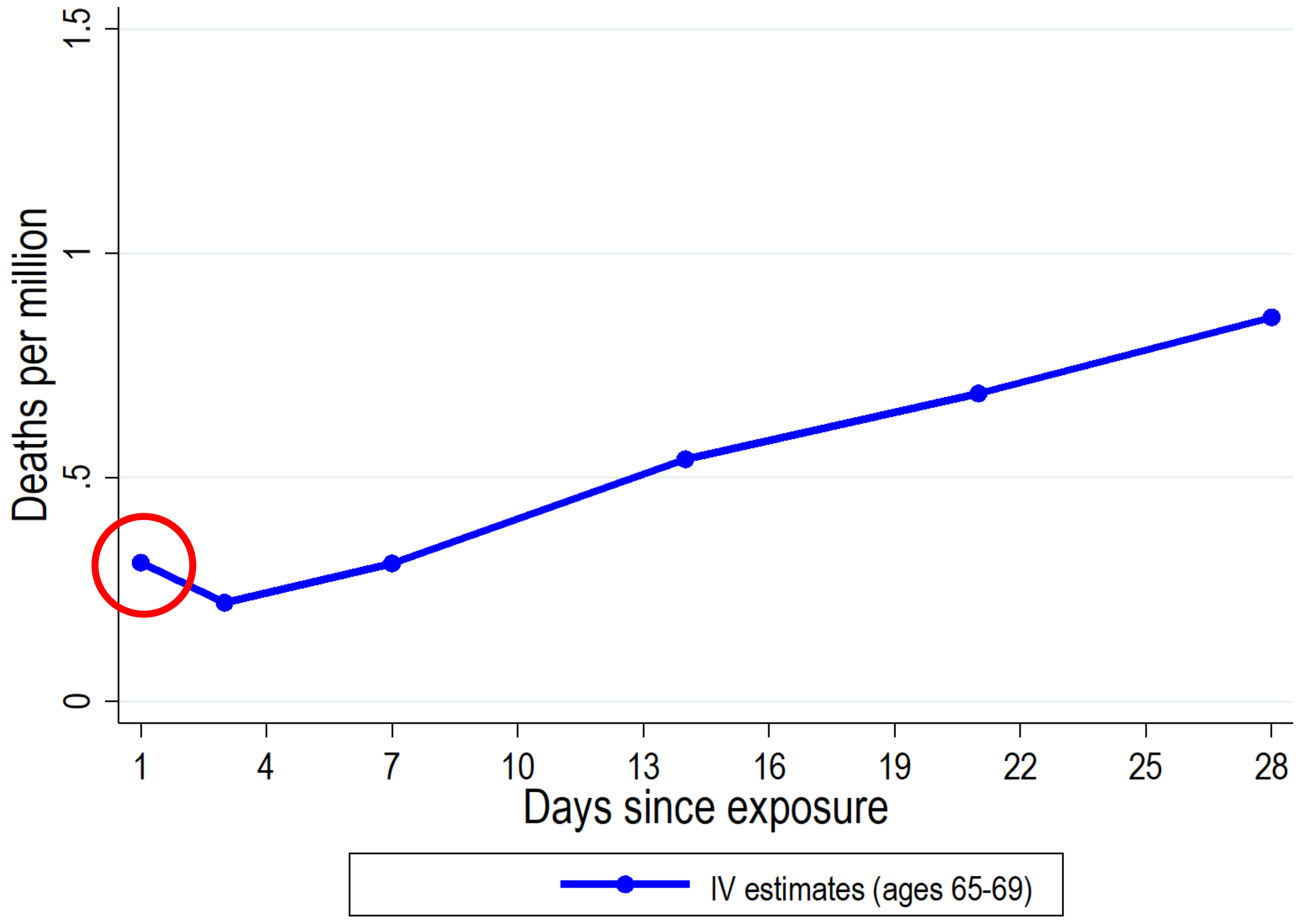
Two ways to match regression estimates of daily mortality:

1. Change in health capital: δ, α, or I
   → short- and long-run effects on mortality
2. Change in death threshold: $\underline{H}$
   → short-run mortality displacement

Cumulative mortality effect for ages 65-69



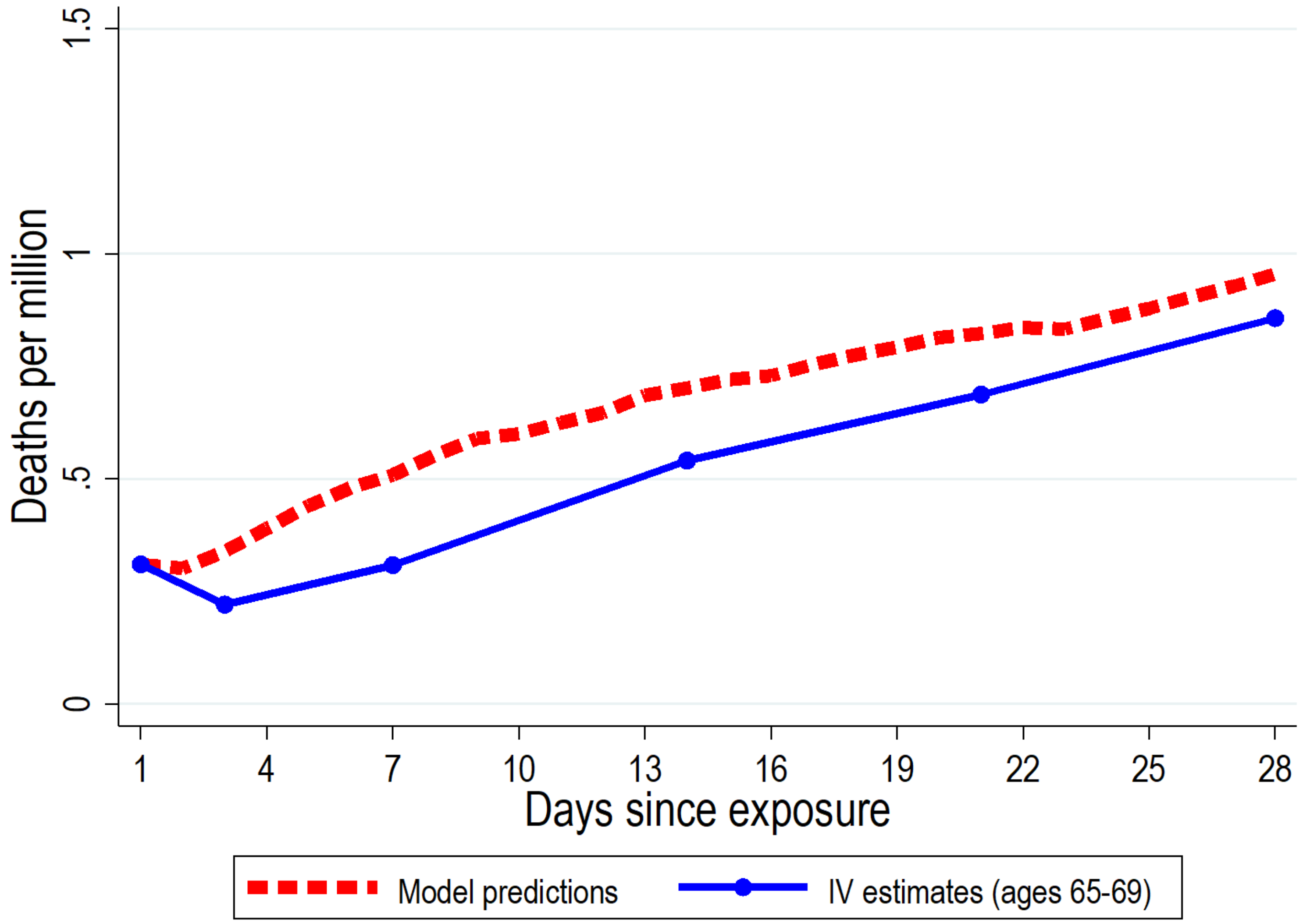
Calibrate model parameters for 1-day effect



Model calibrated to match regression estimate for same-day exposure

Assume half the effect is mortality displacement (increase in $\underline{H}$)

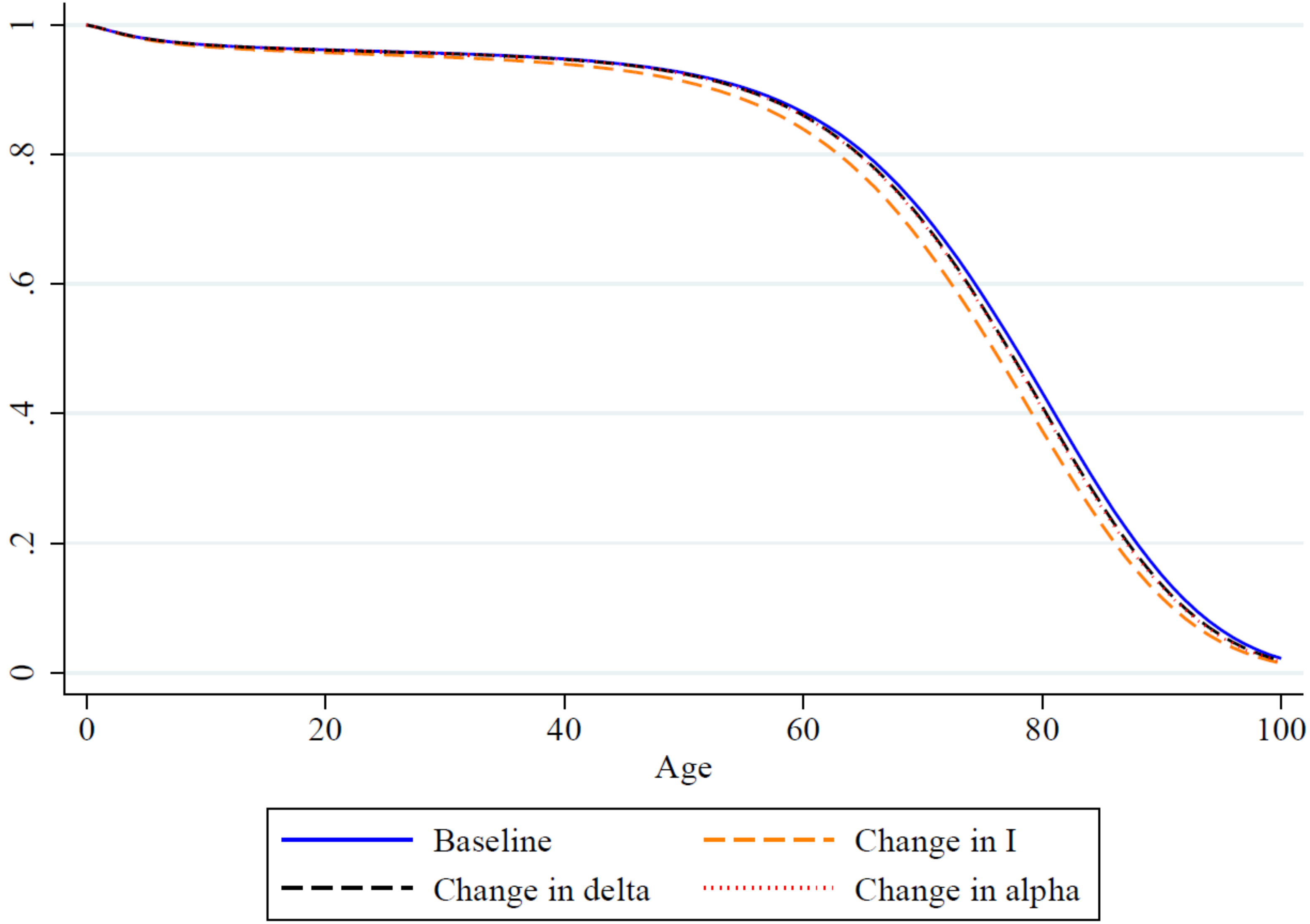
Run model forward for 28 days



Model calibrated to match regression estimate for same-day exposure

Assume half the effect is mortality displacement (increase in $\underline{H}$)

Effect of a permanent 1-unit increase in SO2 on survival



<u>Implied life expectancy</u>

Baseline: 74.8 years

Change in alpha: 74.1

Change in delta: 74.2

Change in I: 72.7

Where do we go from here?

- If quasi-experimental estimates of the effects of air pollution are to supersede correlational estimates, economists need to be able to speak to long-run pollution impacts
- Studies exploiting longer-lasting pollution shocks and/or longer outcome windows are welcome but must grapple with other issues
- Combining well-identified short-run estimates with structural models of health may be a complementary way forward