Health and Labor Market Effects of Air Pollution: Evidence from Wildfire Smoke

September 2022

Paper #1:
A Causal Concentration-Response Function for Air Pollution: Evidence from Wildfire Smoke

September 2022

Nolan Miller (University of Illinois & NBER)
David Molitor (University of Illinois & NBER)
Eric Zou (University of Oregon & NBER)

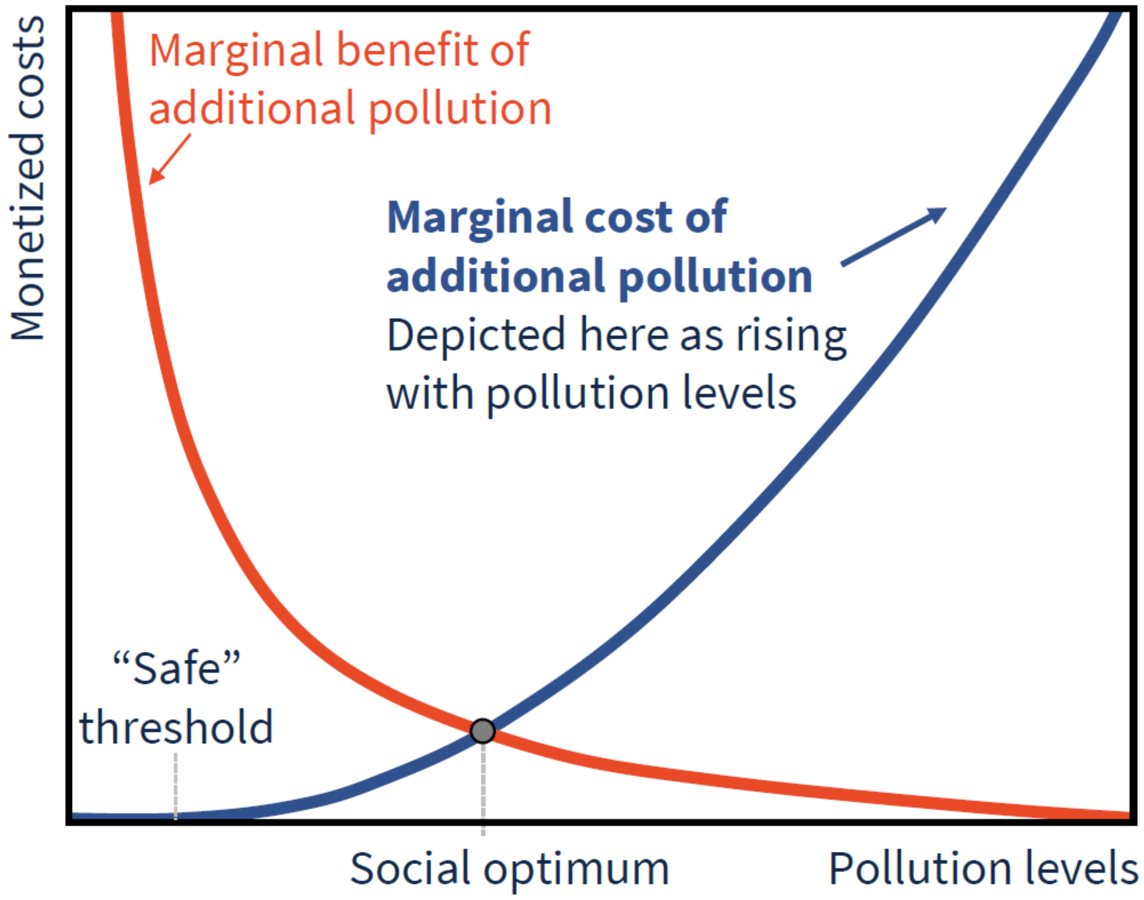
Motivation

- Many countries regulate air pollution to reduce harm to human health
  - Optimal policy equates marginal damages of pollution to marginal abatement costs

- Many studies of air pollution and health
  - Ex: Chay & Greenstone (2003); Currie & Neidell (2005); Chen et al. (2013); Anderson (2020); Knittel et al. (2016); Schlenker & Walker (2016); Deryugina et al. (2019)
  - Typically estimate average effect of "shock"
  - Shape of marginal damage curve?

Optimal Pollution Regulation: Conceptual Framework

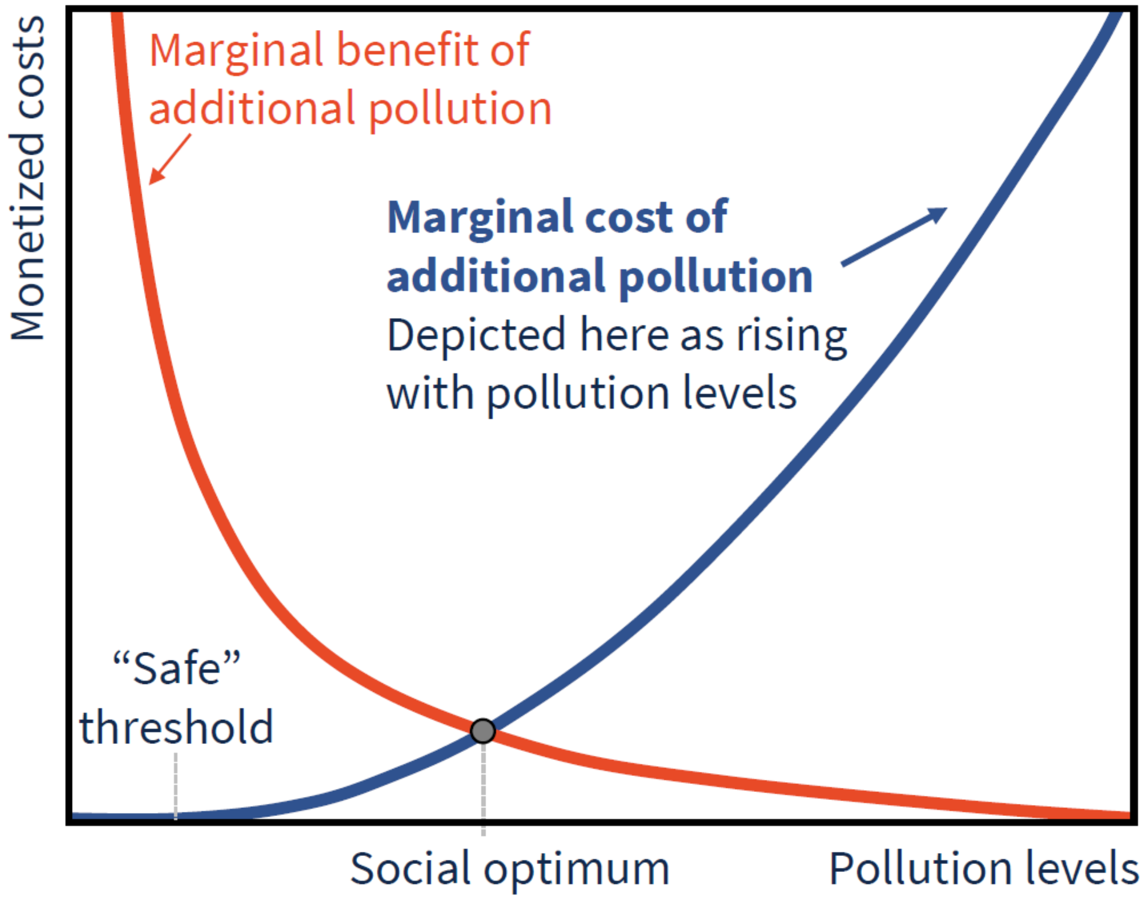
Traditional conceptual framework for economic analysis of marginal cost vs. benefits

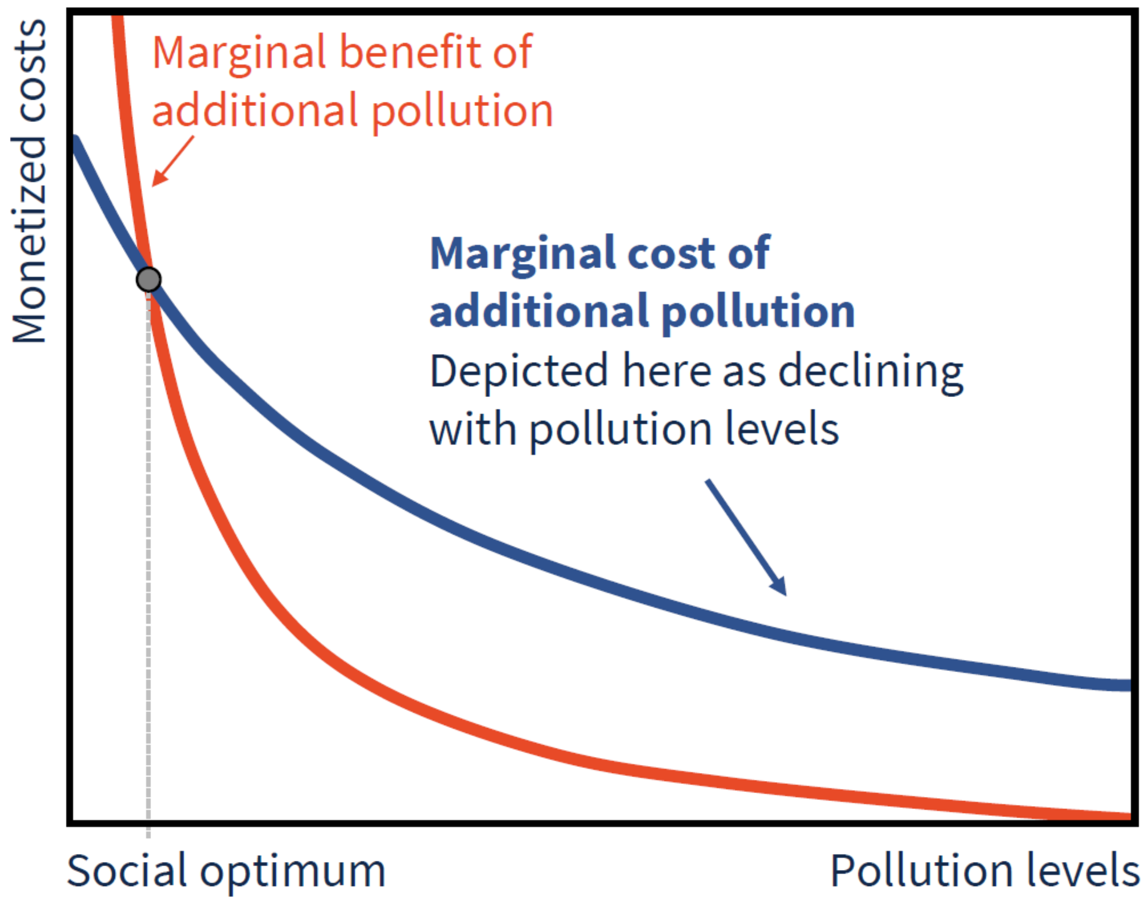


Notes: Adapted from Figure 2(b) of Pope III et al. (2015)

Optimal Pollution Regulation: Conceptual Framework

Traditional conceptual framework for economic analysis of marginal cost vs. benefits



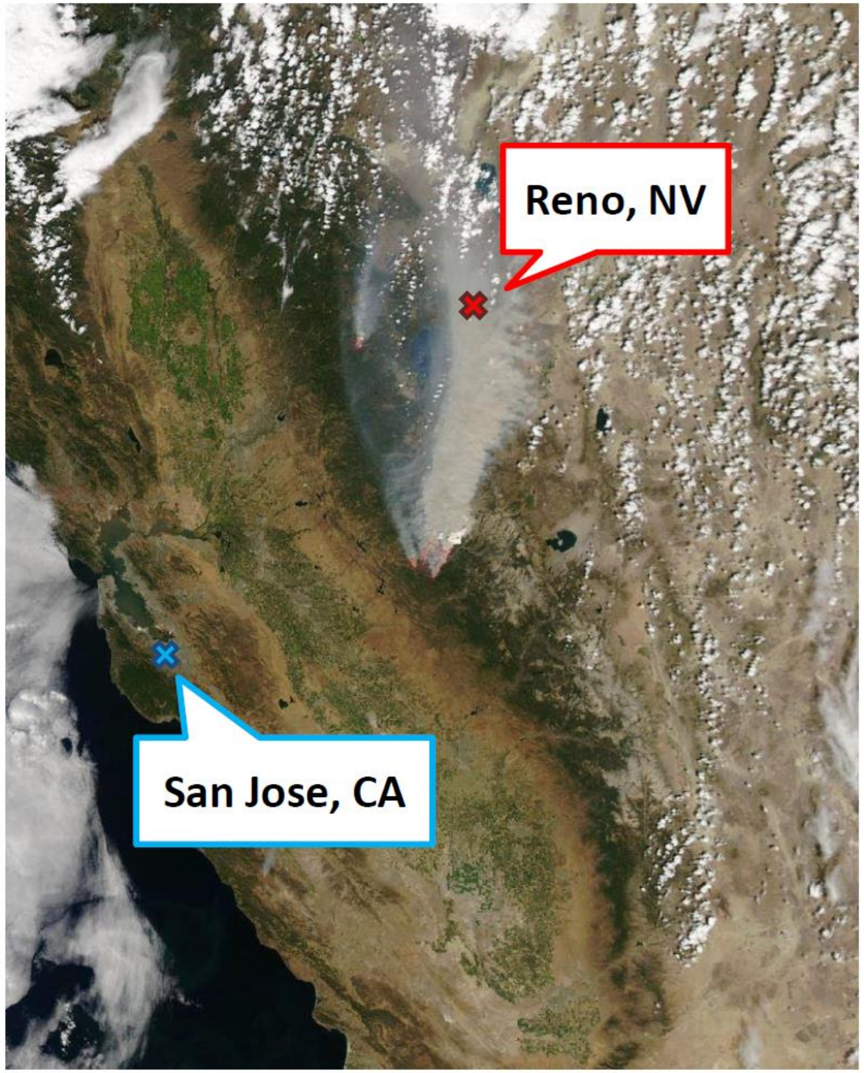


<u>Notes:</u> Adapted from Figure 2(b) of Pope III et al. (2015)

Primary Contributions

- This paper: Estimate impact of wildfire smoke on air quality and U.S. elderly mortality
  - Wildfire smoke is common, can drift 100s of miles
  - Nearly every county experienced some exposure
- Use satellite imaging of smoke plume coverage as instrument for air pollution
  - Smoke transport directly measured—no need for probabilistic transport model or wind
  - Can be used at large spatial scales, even in places with no pollution monitor
- Estimate dose-response function of pollution
  - Exploit variation in large vs. small smoke shock
  - How do health damages rise with exposure?
  - Do low levels of exposure matter for health?

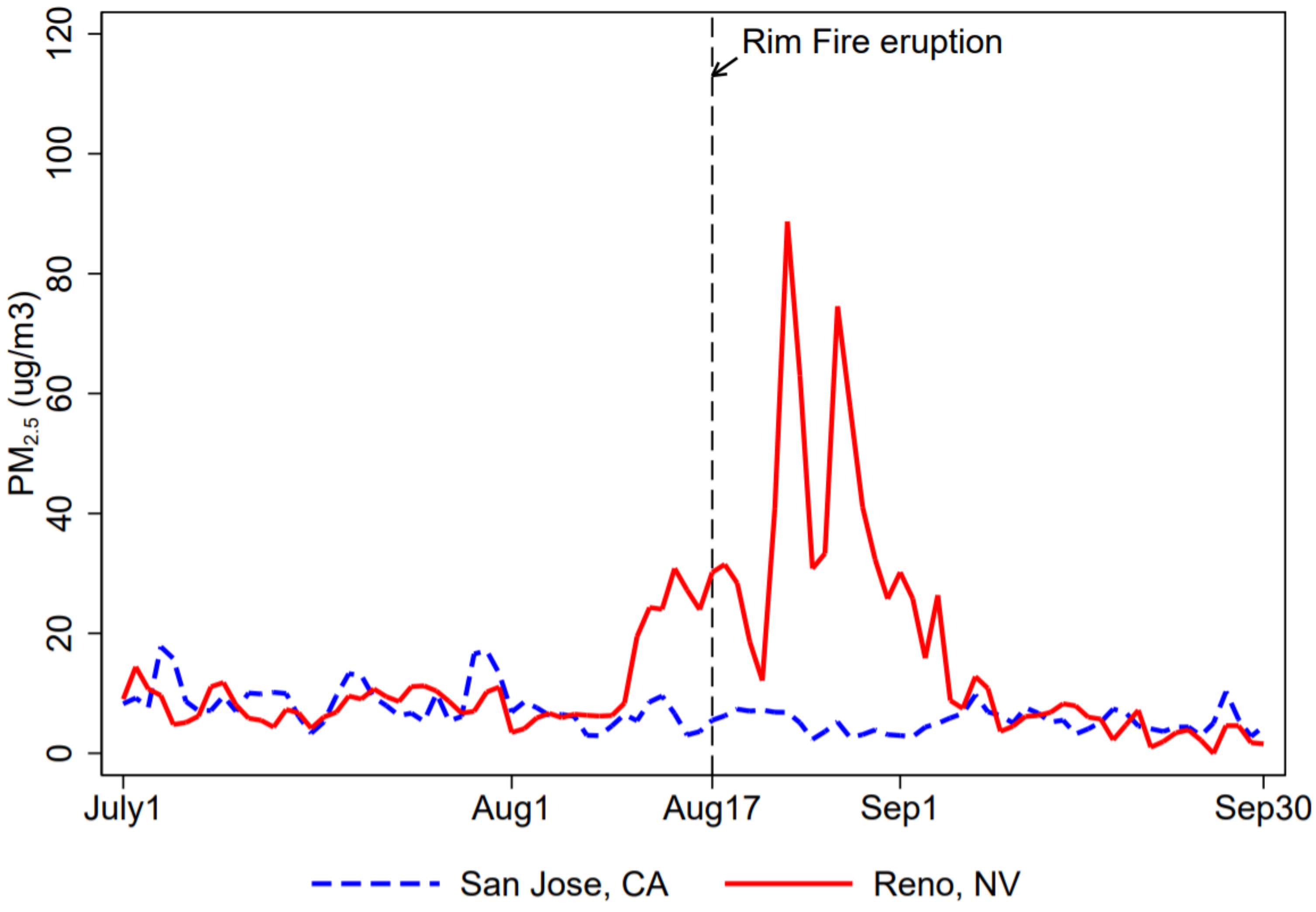
Example: Rim Fire, CA (2013)



Notes: NASA Earth Observatory. August 22, 2013.

Example: Fine Particulate Pollution (PM2.5) in Reno and San Jose

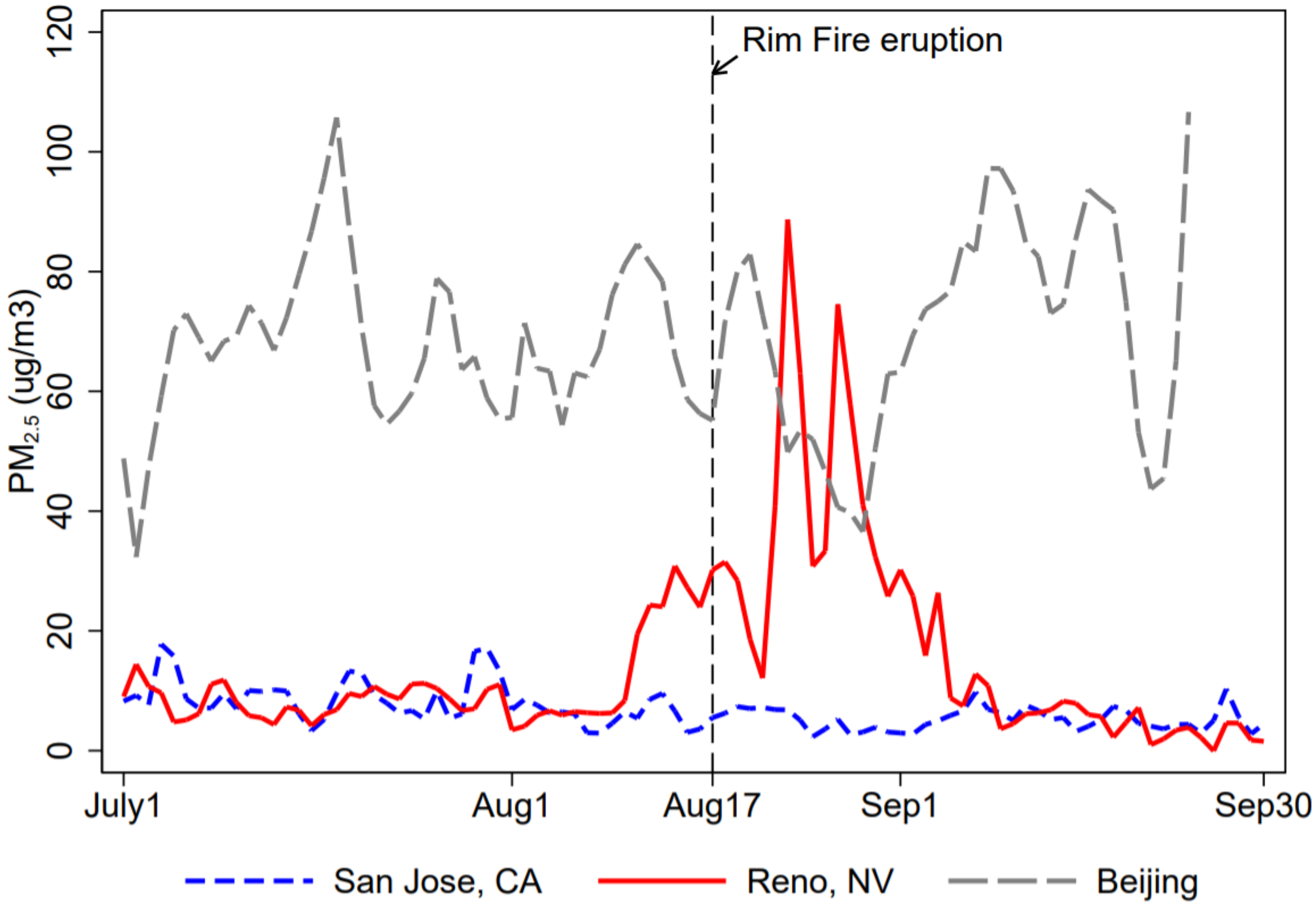
Wildfire smoke substantially elevated PM2.5 in Reno for about a week



Notes: Daily PM2.5 concentration for San Jose, CA and Reno, NV. 5-day moving average PM2.5 is from the U.S. Embassy Beijing Air Quality Monitoring program.

Example: Fine Particulate Pollution (PM2.5) in Reno and San Jose

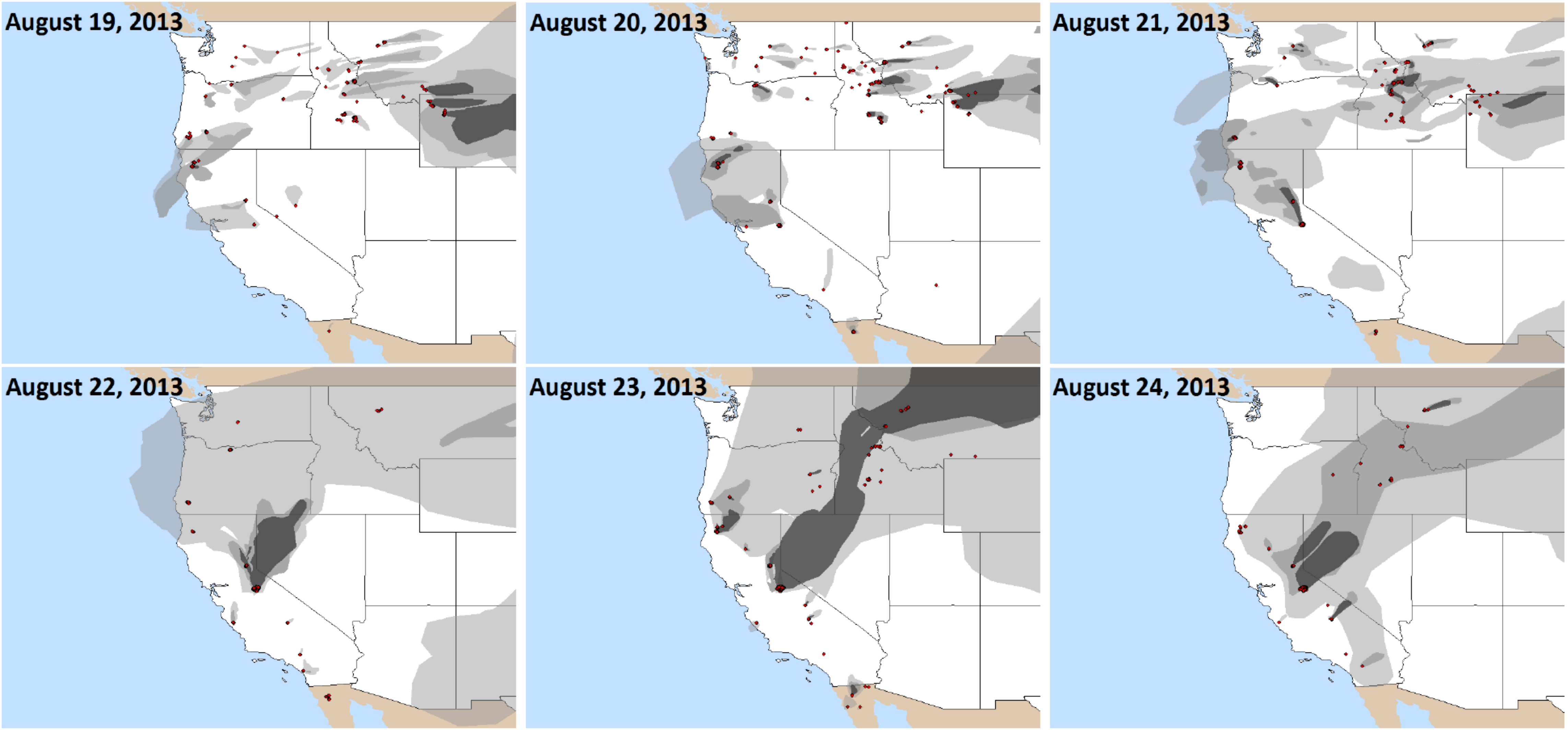
Wildfire smoke substantially elevated PM2.5 in Reno for about a week



<u>Notes:</u> Daily PM2.5 concentration for San Jose, CA and Reno, NV. 5-day moving average PM2.5 is from the U.S. Embassy Beijing Air Quality Monitoring program.

Satellite-based Smoke Data: NOAA Hazard Mapping System

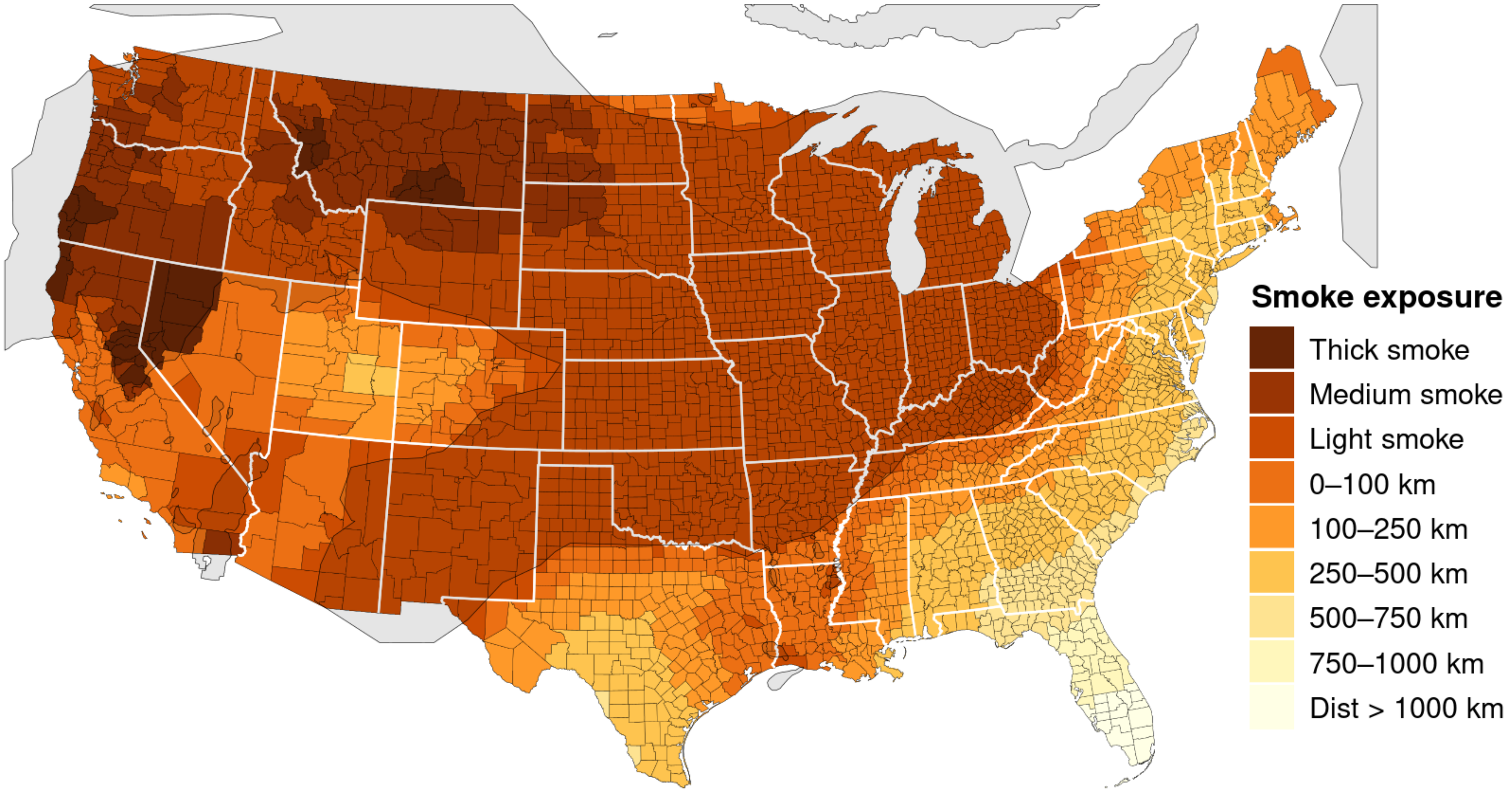
Daily snapshots of the smoke data around the Rim Fire



<u>Notes:</u> Red dots represent ground hot spots detected by the satellite algorithm. Gray polygons outline the smoke extent. Darker contours represent thicker smoke.

Example: Linking smoke plumes to geography

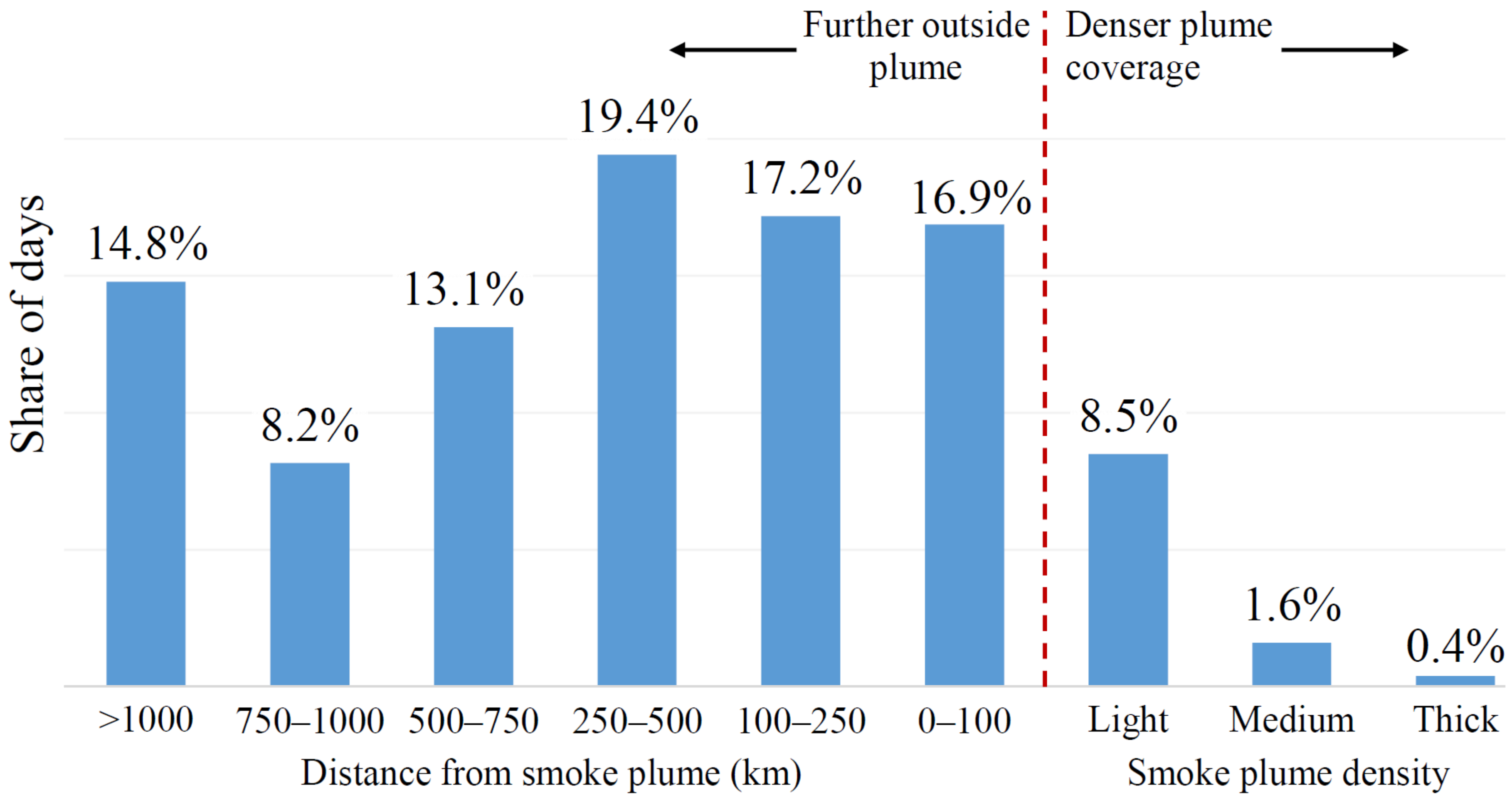
Defining county exposure to smoke, August 22, 2013



Notes: Gray polygons outline the smoke extent. Darker contours represent thicker smoke.

Smoke Shocks: Distribution of Smoke Shocks of Various Intensity

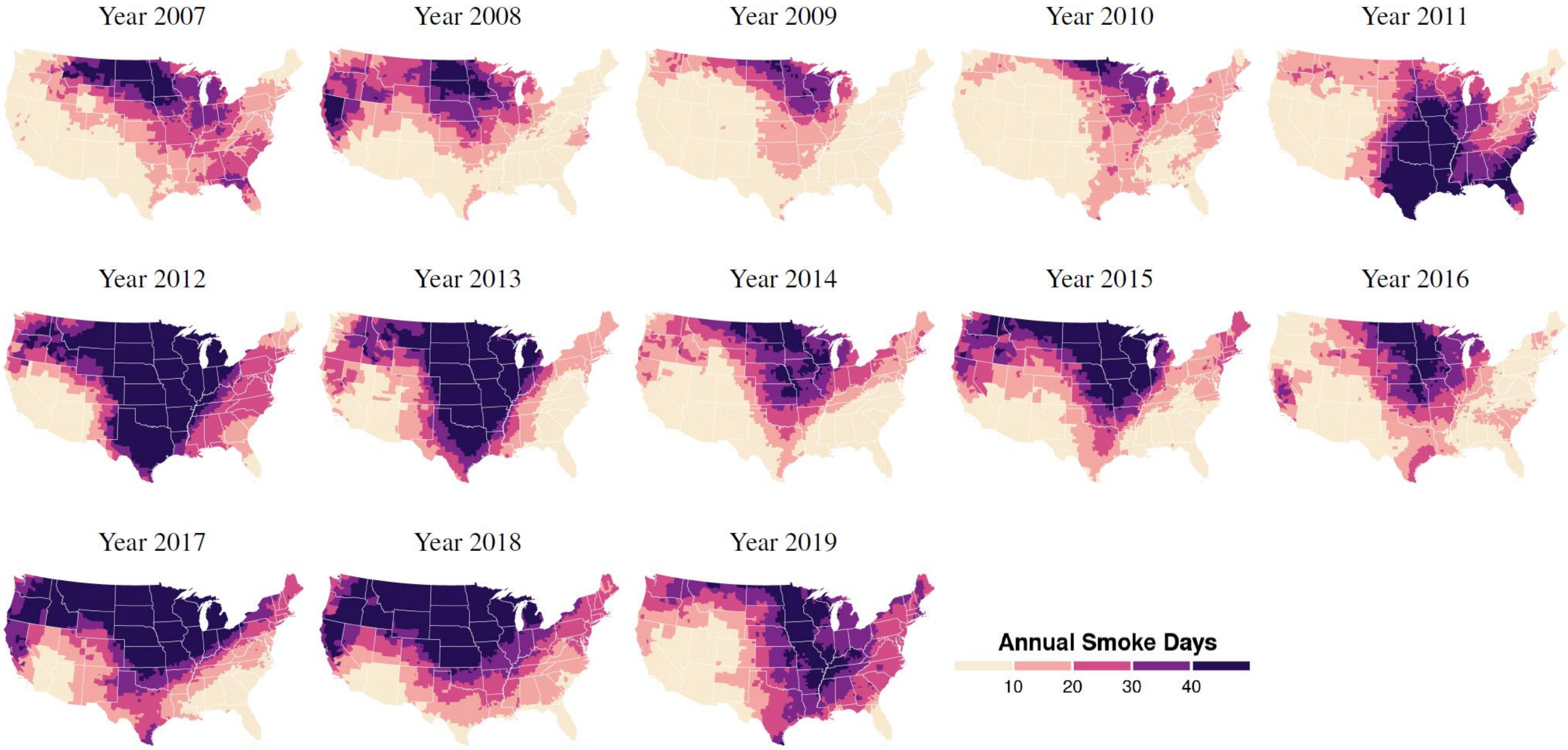
All county-days, 2007-2017



Notes: Observations are for county and date, 2007–2017. Distribution is weighted by Medicare population.

Smoke Shocks: Days of Smoke Coverage by County 2007-2019

Midwest sees the most downwind smoke from California and Canada fires



Notes: This figure plots the number of days of smoke exposure in each county in the continental United States over the 2007-2019 sample period. Average population-weighted exposure during this period was 20.2 days per year.

Data

- Medicare administrative data on 100% of beneficiaries aged 65+, 2007–2017
  - Covers 98% of U.S. population aged 65+
  - One-half billion person-years
  - County of residence and exact date-of-death

- Analysis sample: County × daily panel with mortality rate, environmental data
  - Smoke events
  - Air pollution
  - Temperature, precipitation, wind
  - 13 million observations

Estimating the Impact of Wildfire Smoke

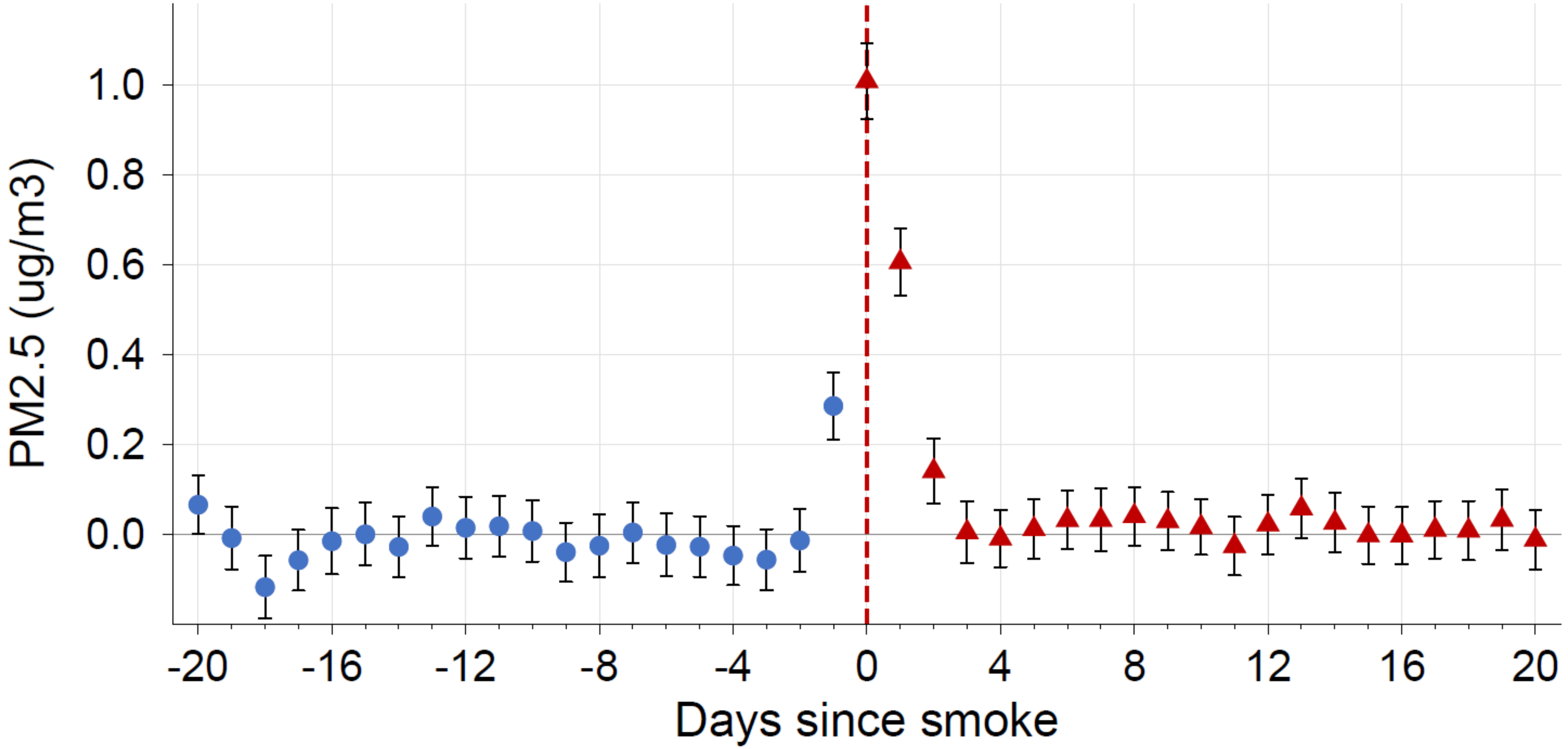
- Event study of smoke:

$$Y_{ct} = \overbrace{\sum_{d\in[-20,20]} \beta_d \cdot \mathrm{Smoke}_{c(t+d)}}^{\text{leads \& lags of smoke}}$$
$$+ [\text{county} \times \text{day} - \text{of} - \text{year FEs}]_{ct} + [\text{state} \times \text{year} \times \text{month}]_{ct} + \varepsilon_{ct}$$

  - Smoke_{ct} = sum of scaled smoke shocks in county c on date t
  - Y_{ct} = ground-level PM2.5 (ug/m3) and mortality (deaths per million)
  - Population weights; 2-way clustered standard errors at the county & date levels

Pollution Event Study: Changes in PM2.5 by Days since Smoke Exposure

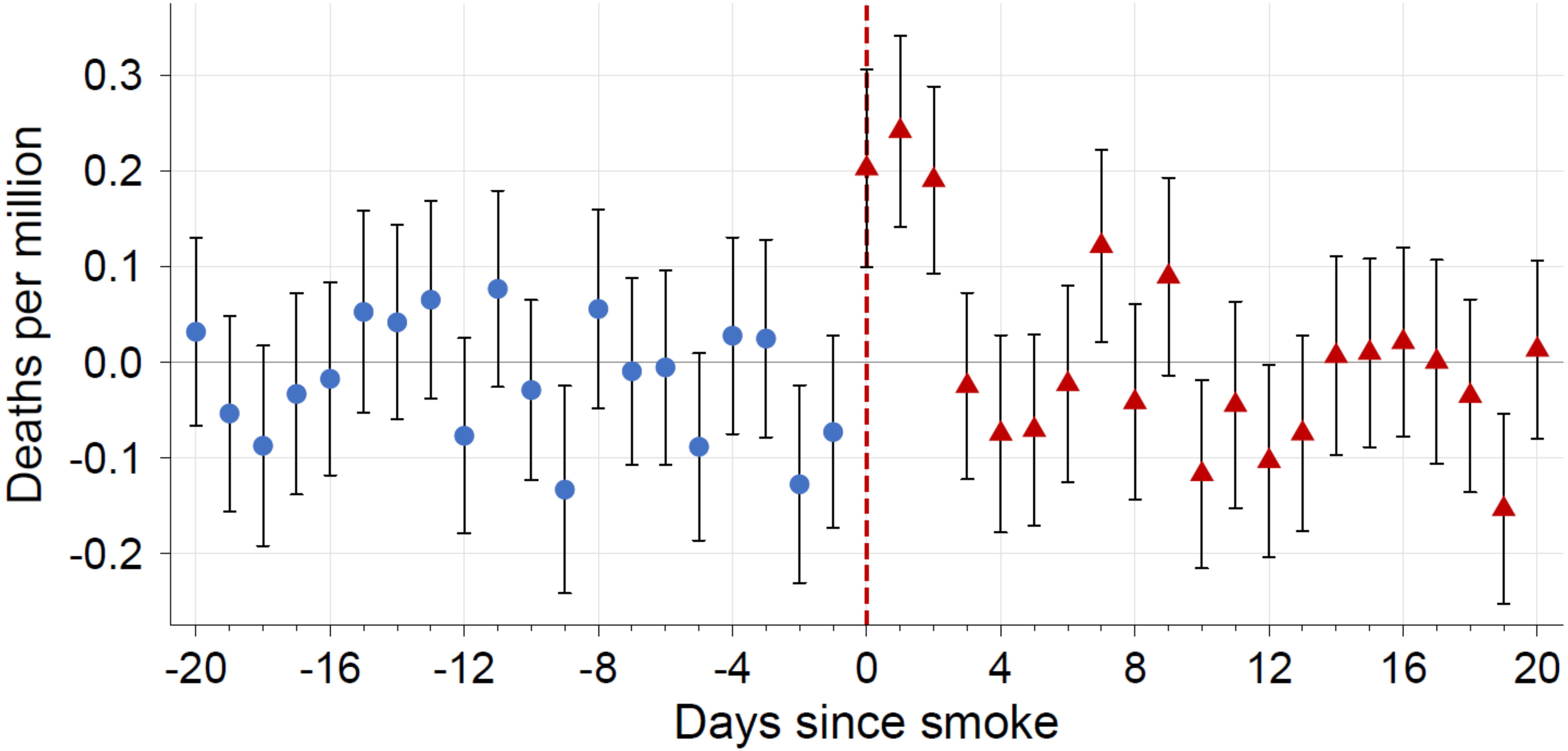
Monitors detect spikes in ground-level PM2.5 when satellites see smoke



Notes: Estimation equation: $[PM_{2.5}]_{cd} = \sum_{\tau=-20}^{20} \beta_\tau \cdot \text{SmokeIndex}_{c,d+\tau} + \alpha_{c\times day-of-year} + \alpha_{state\times year} + \varepsilon_{cd}$. Standard errors are clustered at both the county and the date levels.

Mortality Event Study: Changes in Mortality by Days since Smoke Exposure

Elderly mortality rate spikes upon smoke exposure



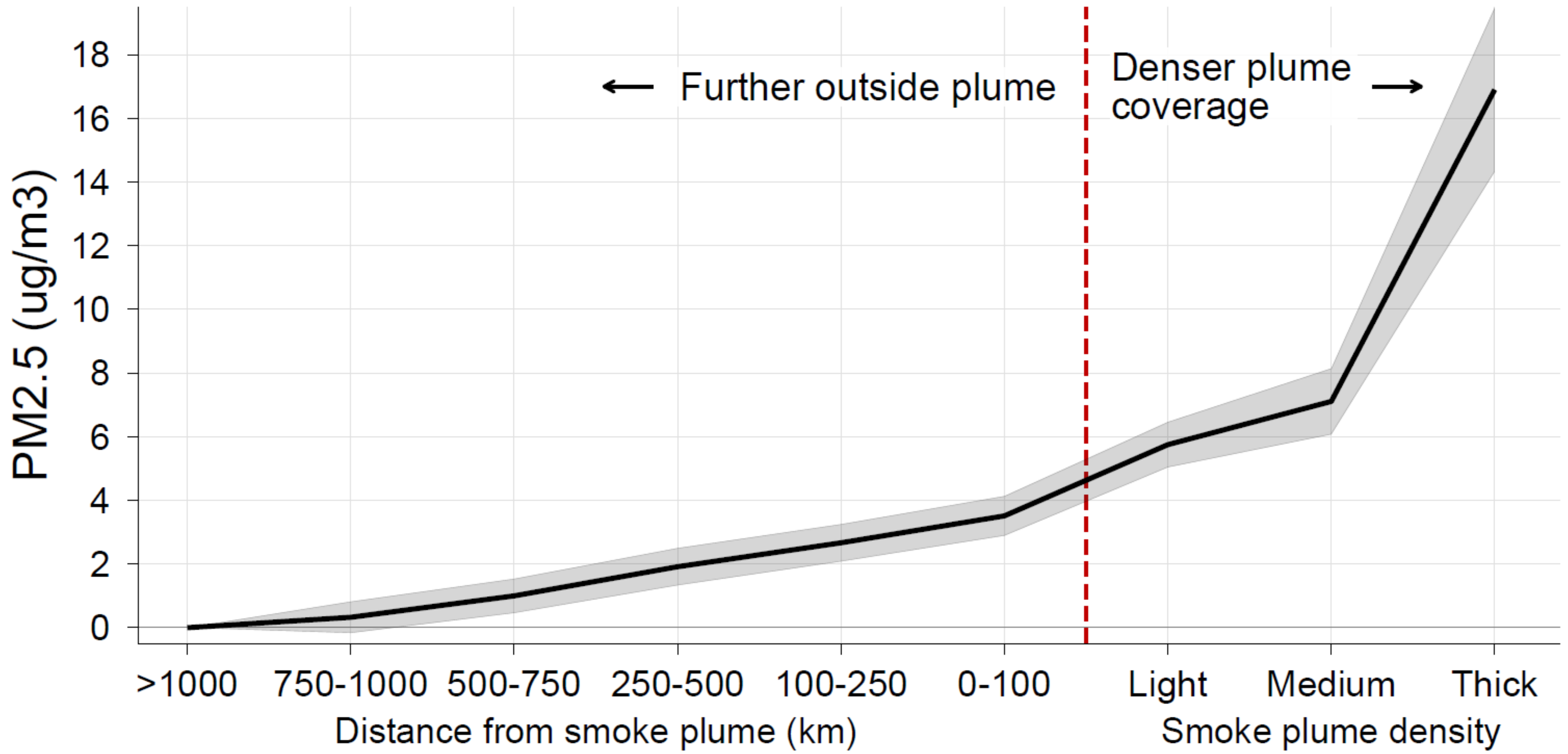
Notes: Estimation equation: $[\text{Mortality}]_{cd} = \sum_{\tau=-20}^{20} \beta_\tau \cdot \text{SmokeIndex}_{c,d+\tau} + \alpha_{c\times\text{day-of-year}} + \alpha_{\text{state}\times\text{year}} + \varepsilon_{cd}$. Standard errors are clustered at both the county and the date levels.

Marginal damages of pollution exposure

- Policy debate: health benefit of reducing air pollution
  - Does low levels of exposure matter for health?
  - Does health damage rise linearly with exposure?
- Empirical challenge: identify quasi-random source of variation in large vs. small pollution shocks
- Our insight: drifting plumes generate quasi-experimental gradient in pollution exposure by distance to smoke

PM2.5 Effects: **Changes in PM2.5 by intensity of smoke shock**

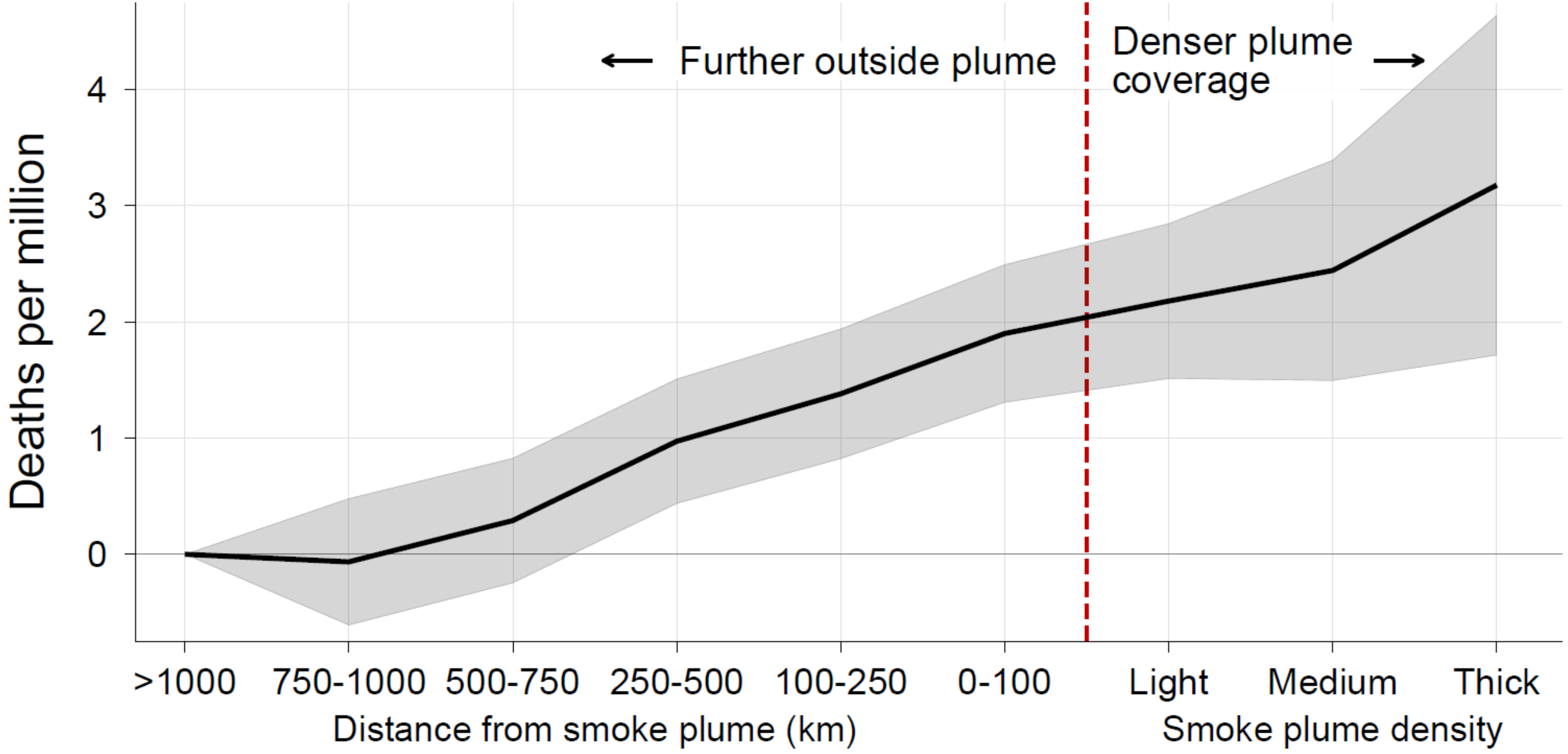
Pollution rises as one gets closer to plumes



Notes: Shaded region shows 95% CIs based on two-way clustering by county and date.

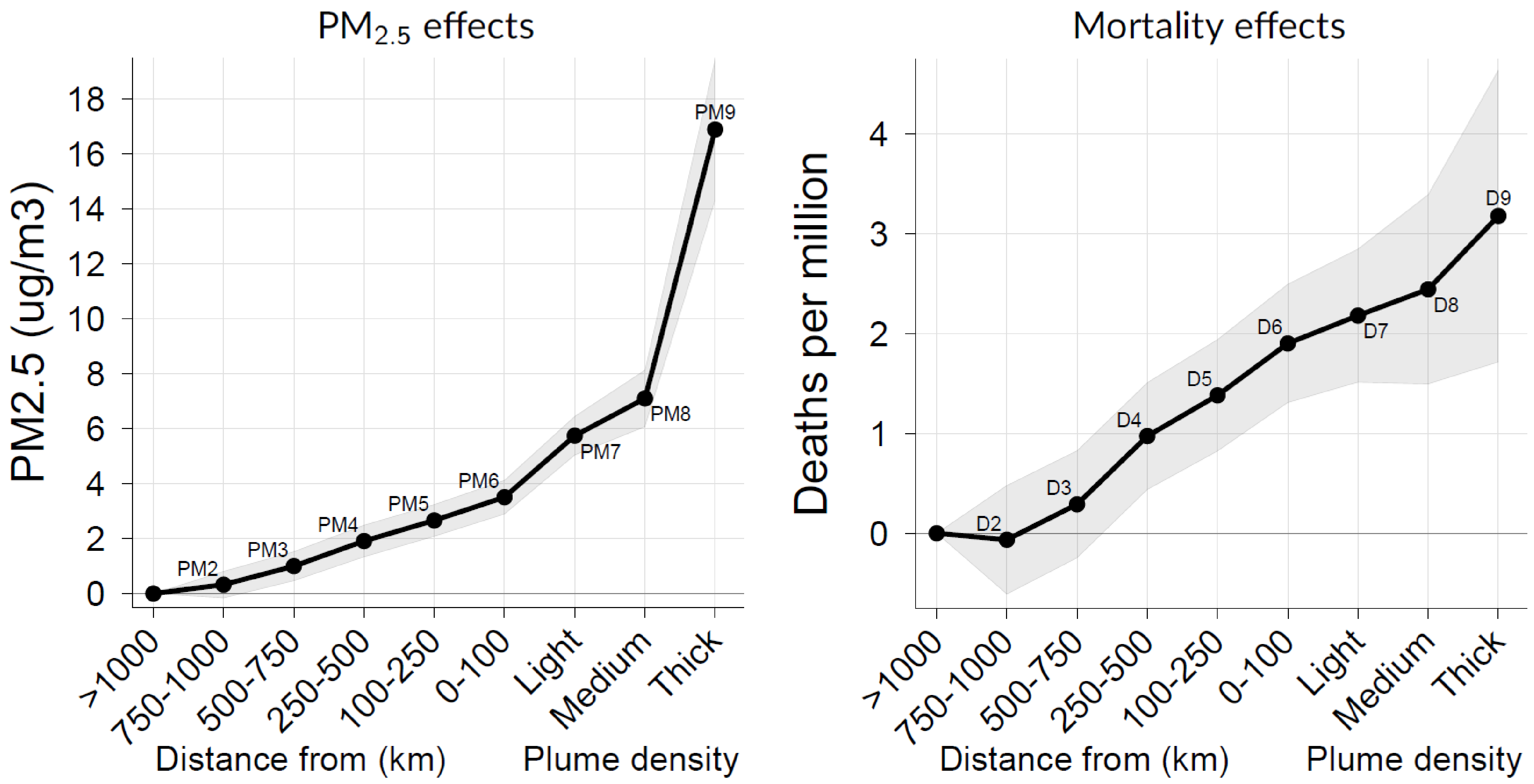
Mortality Effects: Changes in Mortality by intensity of smoke shock

Elderly death rate rises as one gets closer to plumes



Notes: Shaded region shows 95% CIs based on two-way clustering by county and date.

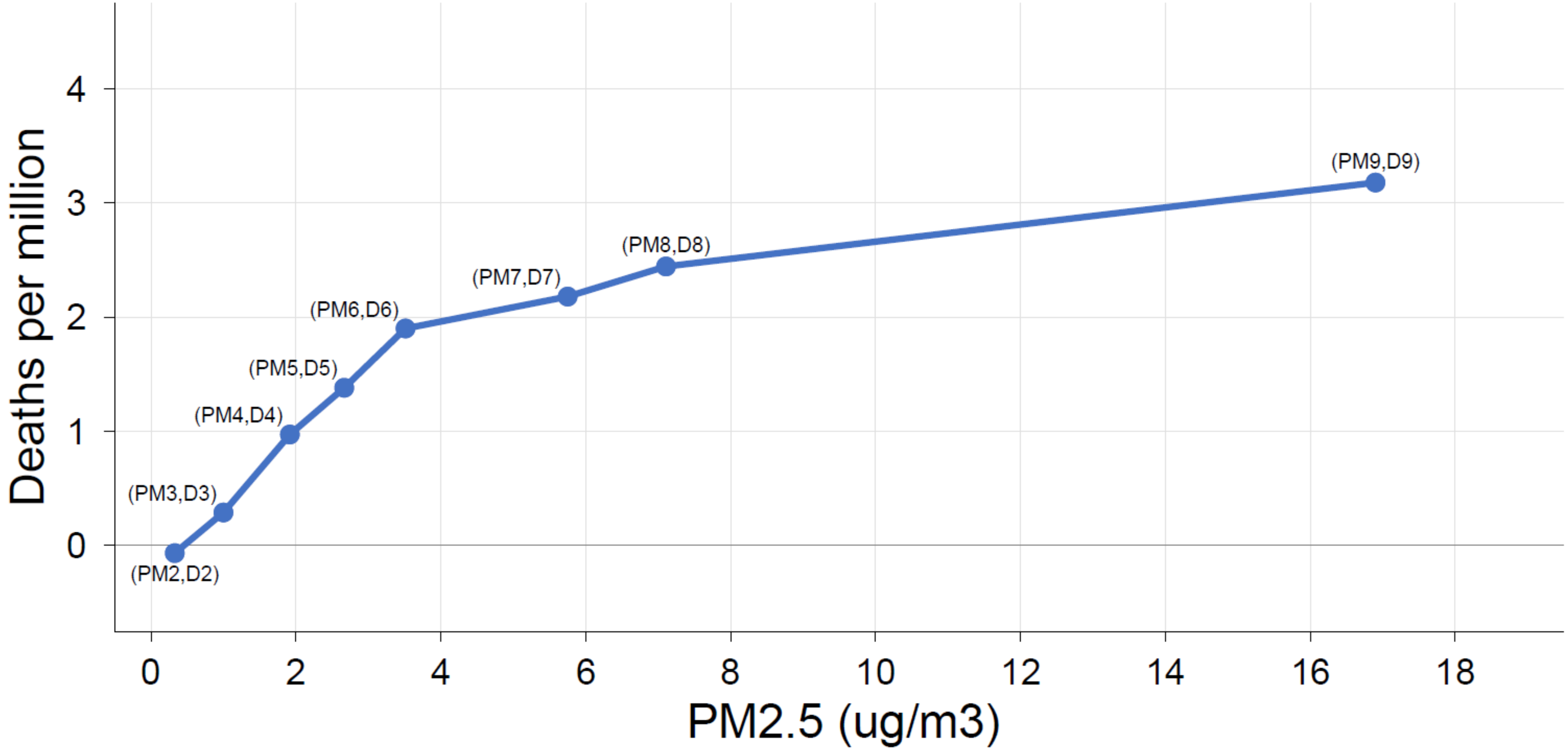
Concentration-Response Function: Elderly Mortality vs. PM2.5



<u>Notes:</u> Shaded region shows 95% CIs based on two-way clustering by county and date.

Concentration-Response Function: Elderly Mortality vs. PM2.5

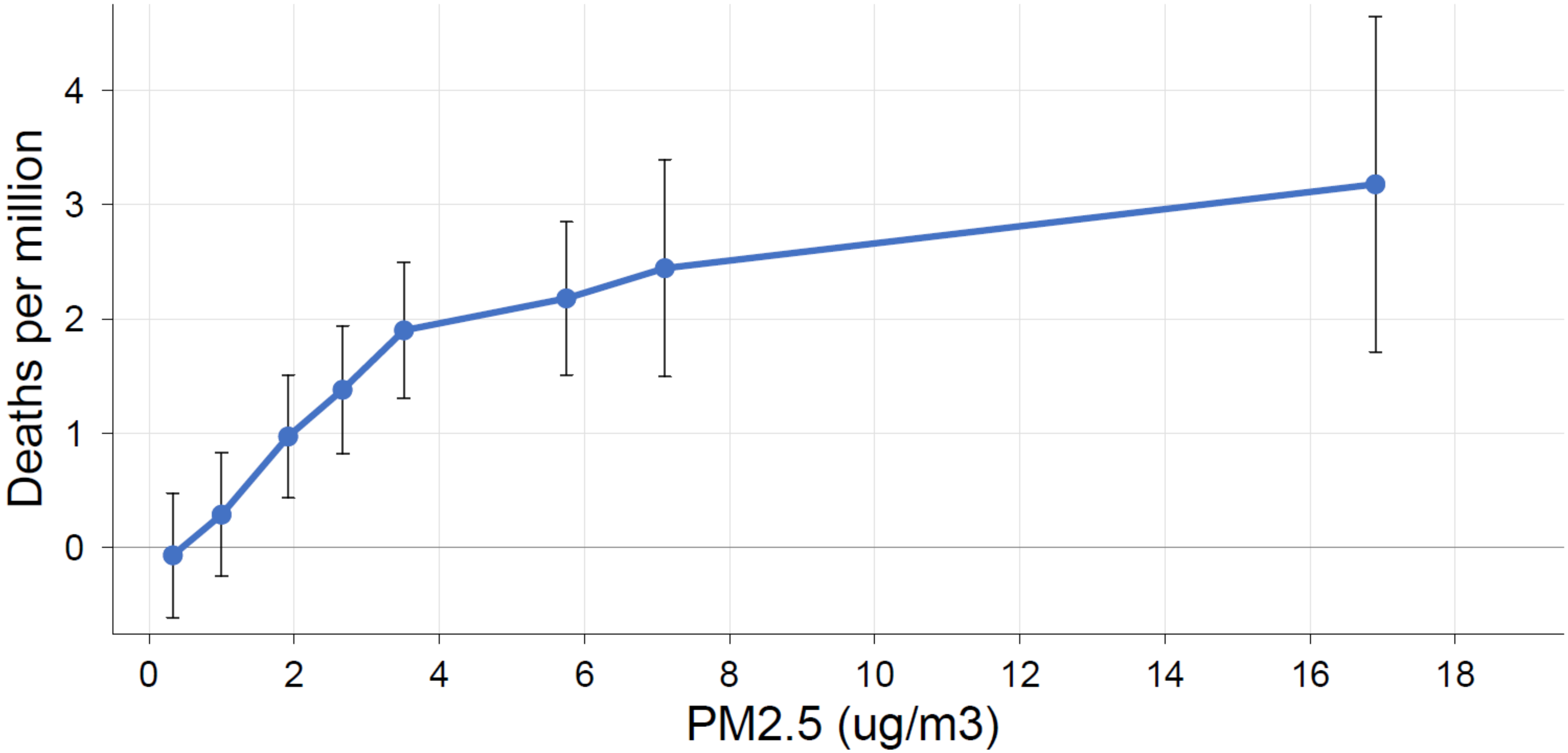
Wildfire smoke quasi-experiments suggest concave concentration-response function



<u>Notes:</u> Shaded region shows 95% CIs based on two-way clustering by county and date.

Concentration-Response Function: Elderly Mortality vs. PM2.5

Wildfire smoke quasi-experiments suggest concave concentration-response function



Notes: Range bars show 95% CIs of mortality effects based on two-way clustering by county and date.

IV Estimates: The Effect of PM2.5 on Elderly Mortality

IV model identifies larger marginal mortality effects from smaller pollution shocks (Concavity)

IV design:	Large shocks (1)	Small shocks (2)	All shocks (3)	Wind (4)
Dependent variable: 3-day deaths per million				
1-day $PM_{2.5}$	0.31***	1.06***	0.62***	0.69***
	(0.09)	(0.15)	(0.08)	(0.06)
	[0.13, 0.49]	[0.76, 1.36]	[0.47, 0.78]	[0.57, 0.80]
Excl. smoke instruments	Large	Small	All	N/A
Incl. smoke instruments	None	Large	None	N/A
F-statistic	13783.5	5998.5	8962.5	298
Dep. var. mean	357	3579	357	385
Obs.	3,478,165	3,478,165	3,478,165	1,980,549

Notes: All IV regressions control for county-day and state-year-month fixed effects and 2 leads/lags of all smoke shocks. OLS replaces smoke shocks with PM2.5. Standard errors are clustered at the county and date levels.

IV Estimates: The Effect of PM2.5 on Elderly Mortality

IV model identifies larger marginal mortality effects from smaller pollution shocks (Concavity)

IV design:	Large shocks (1)	Small shocks (2)	All shocks (3)	Wind (4)
Dependent variable: 3-day deaths per million				
1-day $PM_{2.5}$	0.31***	1.06***	0.62***	0.69***
	(0.09)	(0.15)	(0.08)	(0.06)
	[0.13, 0.49]	[0.76, 1.36]	[0.47, 0.78]	[0.57, 0.80]
Excl. smoke instruments	Large	Small	All	N/A
Incl. smoke instruments	None	Large	None	N/A
F-statistic	13783.5	5998.5	8962.5	298
Dep. var. mean	357	3579	357	385
Obs.	3,478,165	3,478,165	3,478,165	1,980,549

- Using larger pollution shocks as IVs lead to smaller estimates of marginal effects

Notes: All IV regressions control for county-day and state-year-month fixed effects and 2 leads/lags of all smoke shocks. OLS replaces smoke shocks with PM2.5. Standard errors are clustered at the county and date levels.

IV Estimates: The Effect of PM2.5 on Elderly Mortality

IV model identifies larger marginal mortality effects from smaller pollution shocks (Concavity)

IV design:	Large shocks (1)	Small shocks (2)	All shocks (3)	Wind (4)
Dependent variable: 3-day deaths per million				
1-day $PM_{2.5}$	0.31***	1.06***	0.62***	0.69***
	[illegible]	(0.15)	(0.08)	(0.06)
	[illegible]	[0.76, 1.36]	[0.47, 0.78]	[0.57, 0.80]
Excl. smoke instruments	Large	Small	All	N/A
Incl. smoke instruments	None	Large	None	N/A
F-statistic	13783.5	5998.5	8962.5	298
Dep. var. mean	357	3579	357	385
Obs.	3,478,165	3,478,165	3,478,165	1,980,549

- On average, 1 ug/m3 PM2.5 increase elderly mortality by 0.62 deaths per million people

Notes: All IV regressions control for county-day and state-year-month fixed effects and 2 leads/lags of all smoke shocks. OLS replaces smoke shocks with PM2.5. Standard errors are clustered at the county and date levels.

IV Estimates: The Effect of PM2.5 on Elderly Mortality

IV model identifies larger marginal mortality effects from smaller pollution shocks (Concavity)

IV design:	Large shocks (1)	Small shocks (2)	All shocks (3)	Wind (4)
Dependent variable: 3-day deaths per million				
1-day $PM_{2.5}$	[illegible]	1.06***	0.62***	0.69***
	[illegible]	[illegible]	(0.08)	(0.06)
	[illegible]	[illegible]	[0.47, 0.78]	[0.57, 0.80]
Excl. smoke instruments	Large	Small	All	N/A
Incl. smoke instruments	None	Large	None	N/A
F-statistic	13783.5	[illegible]	8962.5	298
Dep. var. mean	357	[illegible]	357	385
Obs.	3,478,165	3,478,165	3,478,165	1,980,549

- Our average estimate is similar to Deryugina et al. (2019 AER) that also uses Medicare data, but uses a different research design (using changes in local wind directions to instrument for PM2.5)

Notes: All IV regressions control for county-day and state-year-month fixed effects and 2 leads/lags of all smoke shocks. OLS replaces smoke shocks with PM2.5. Standard errors are clustered at the county and date levels.

Takeaway #1: The Contribution of Wildfire Smoke to Mortality

- Wildfire smoke dose curve implies about 17,300 premature elderly deaths per year
  - Wildfire smoke accounts for 0.8% of all elderly deaths
  - Assuming a $10 million VSL ($2021, per EPA): $173 billion mortality cost
  - Assuming 3.5 life years lost per decedent (Deryugina et al. 2019): $6 billion cost

- Other costs and losses of wildfires (National Institute of Standards and Technology, 2017)
  - Damage to structures: $617 million
  - Federal + state suppression and protection costs: $3.5 billion

Takeaway #2: Dose-Response Function of Air Pollution

- Wildfire smoke shocks indicate diminishing marginal health damages of air pollution
  - Long-run and non-mortality costs not accounted for here
  - Results point to large benefits of additional air quality improvements in the US
  - Results demonstrate how estimated pollution effects depend on identifying variation

Takeaway #3: How to Calculate Death Toll from Wildfire

- What is the national damage of a local fire event?

- We combine causal estimate and smoke plumes data to predict national mortality damage for each fire

- Now, illustrate this exercise among the largest wildfires in California's history

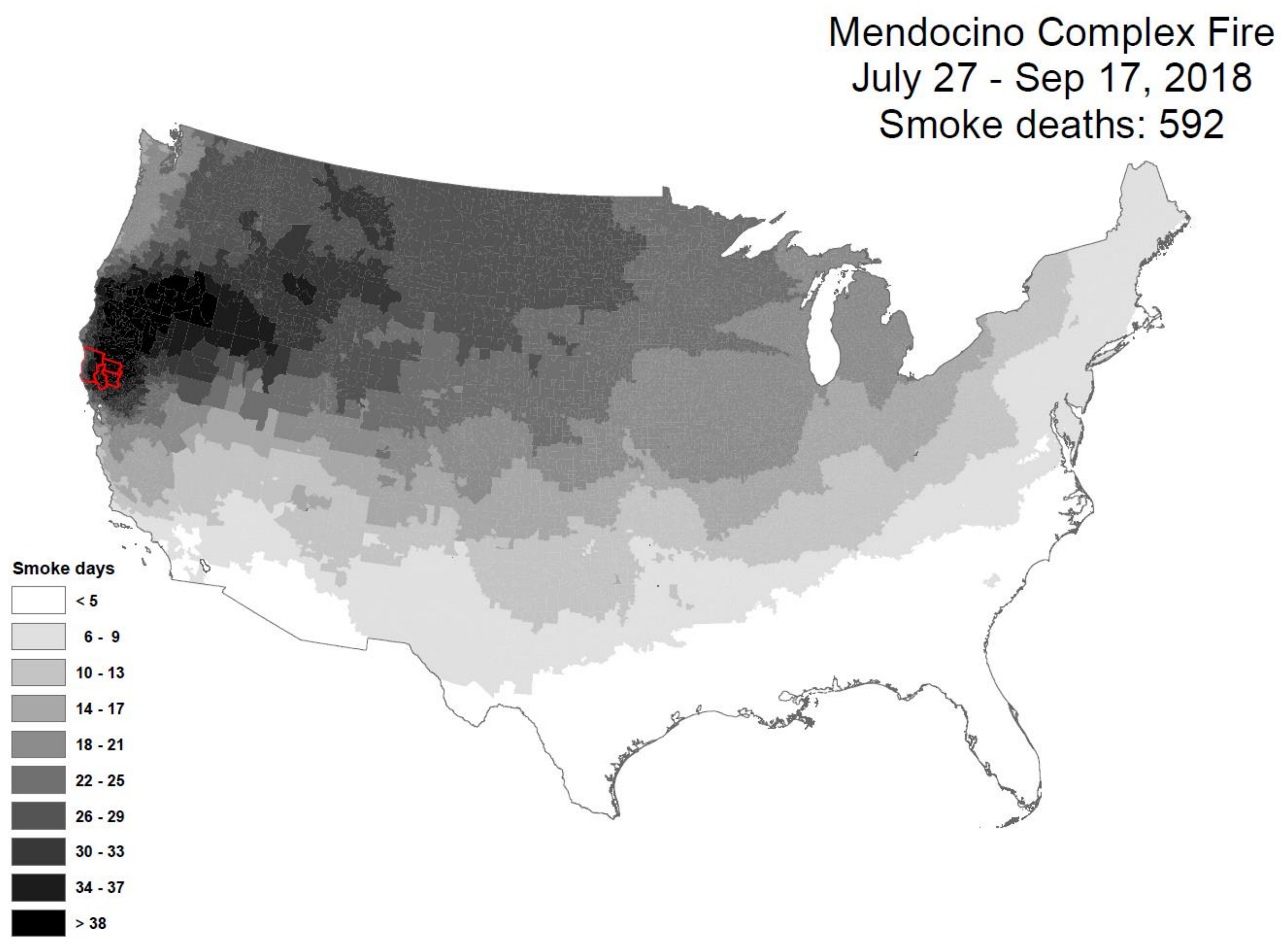
Example: Mendocino Complex Fire (Jul 27-Sep 17, 2018)

Burned area: 459,123 acres
Suppression cost: $200 million
Fatalities: 1 fire fighter

Source: KymKemp.

Smoke Data: Exposure to Mendocino Complex Fire Smoke

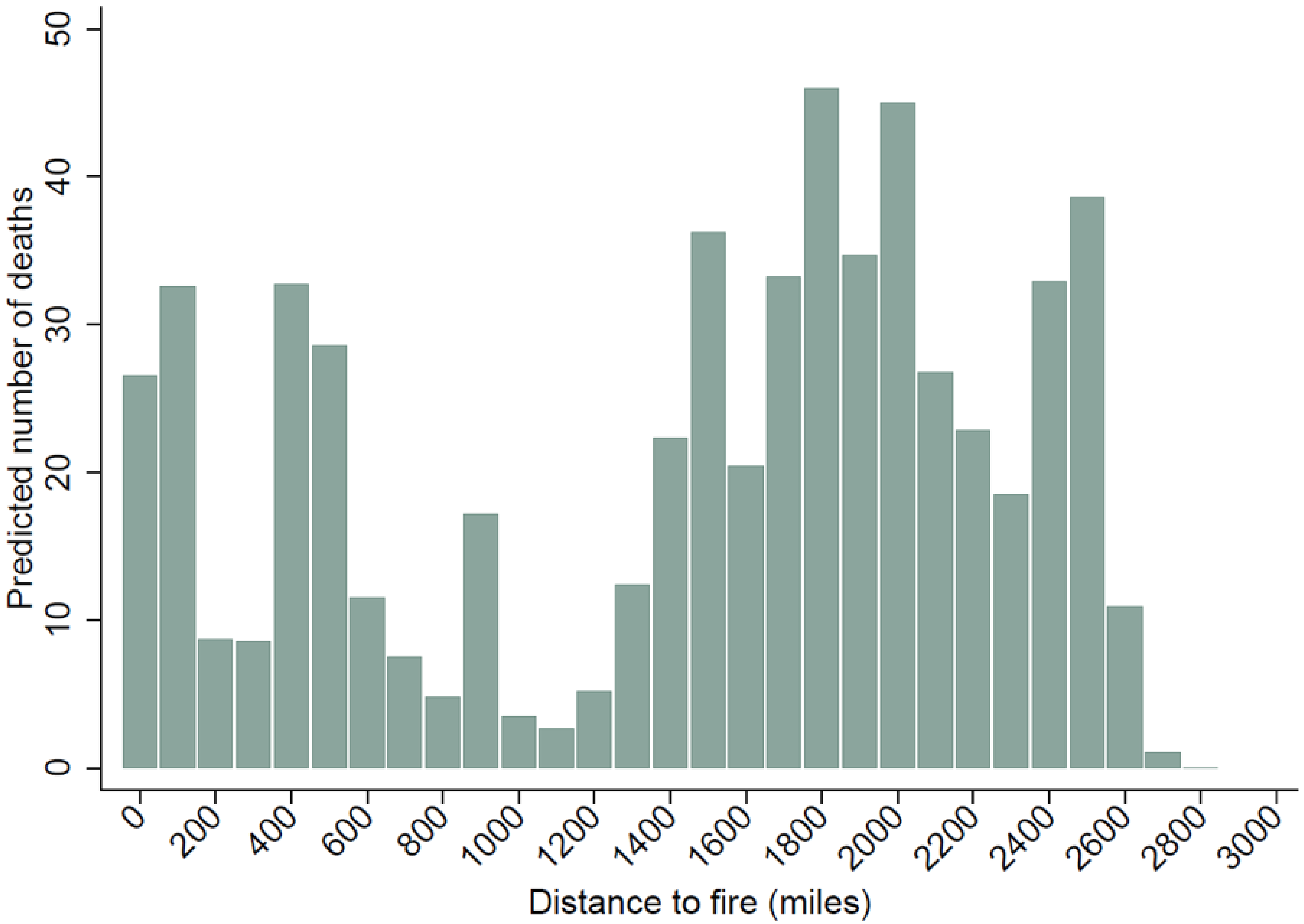
Number of days areas are exposed to smoke plumes linked to the Mendocino Fire



Source: Numbers represent days during the fire period when ZIP Codes are exposed to smoke plumes that intersect fire counties (Mendocino, Colusa, Lake, Glenn).

Mortality Distribution: Predicted Smoke Deaths by Distance to Fire

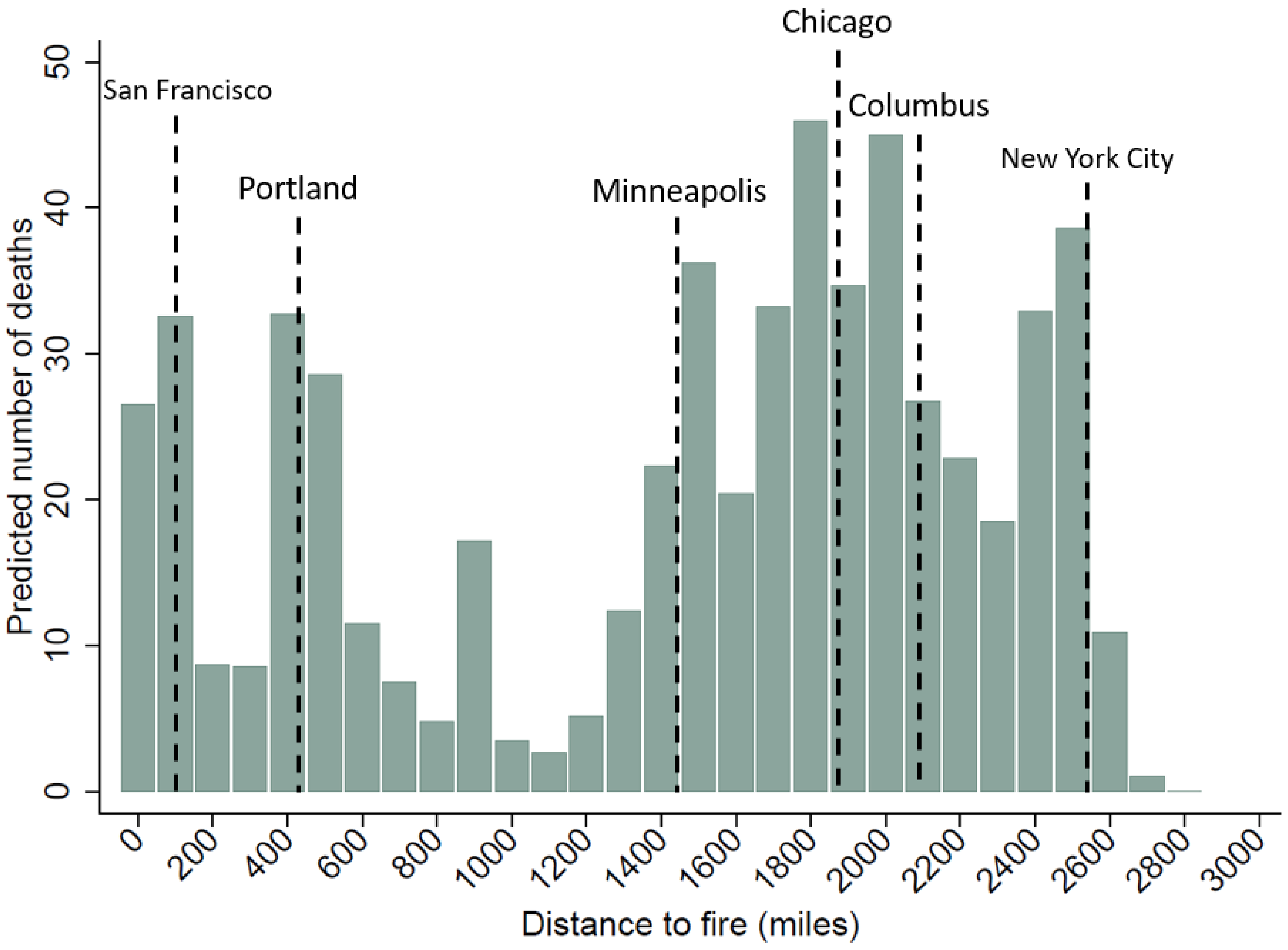
Bulk of mortality burden of the Mendocino Complex Fire was born by the Midwest



Source: Prediction is based on a 3-day mortality effect estimate of 1.2 deaths per million Medicare population per smoke day.

Mortality Distribution: Predicted Smoke Deaths by Distance to Fire

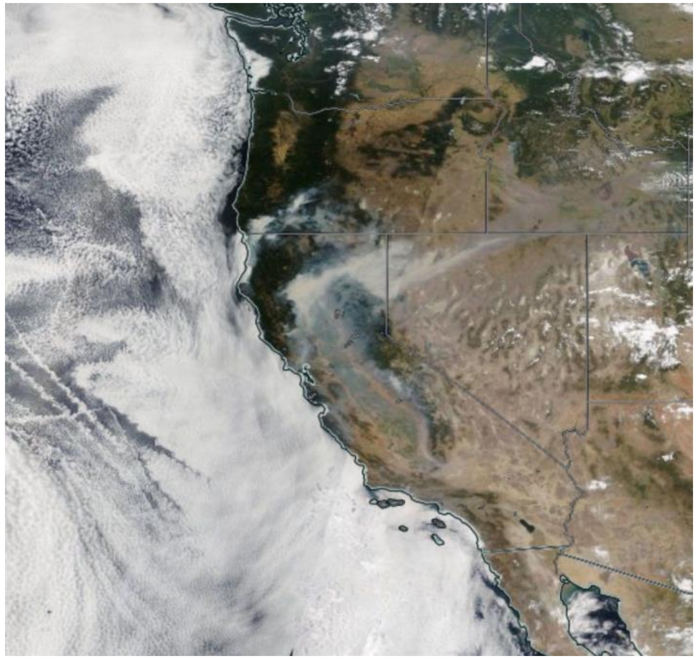
Bulk of mortality burden of the Mendocino Complex Fire was born by the Midwest

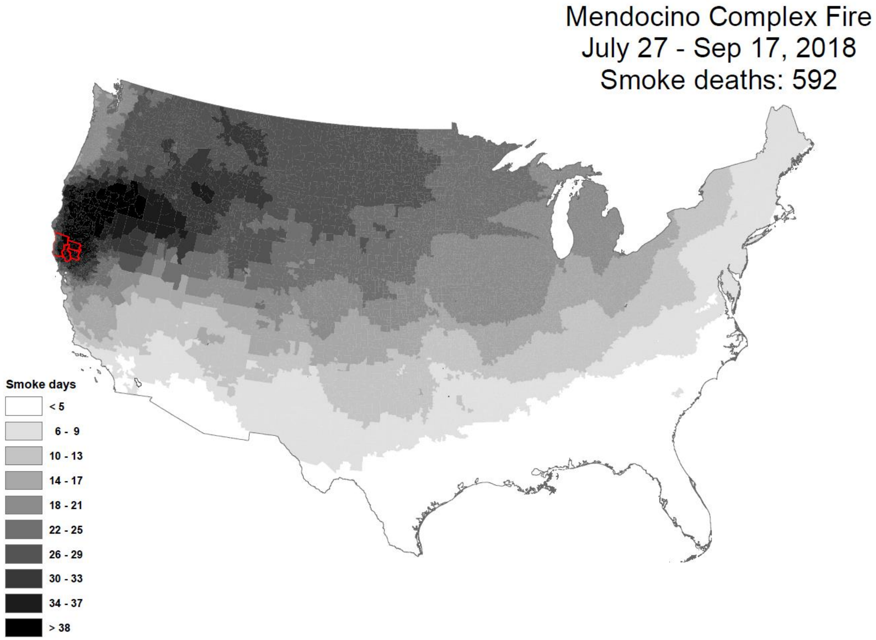


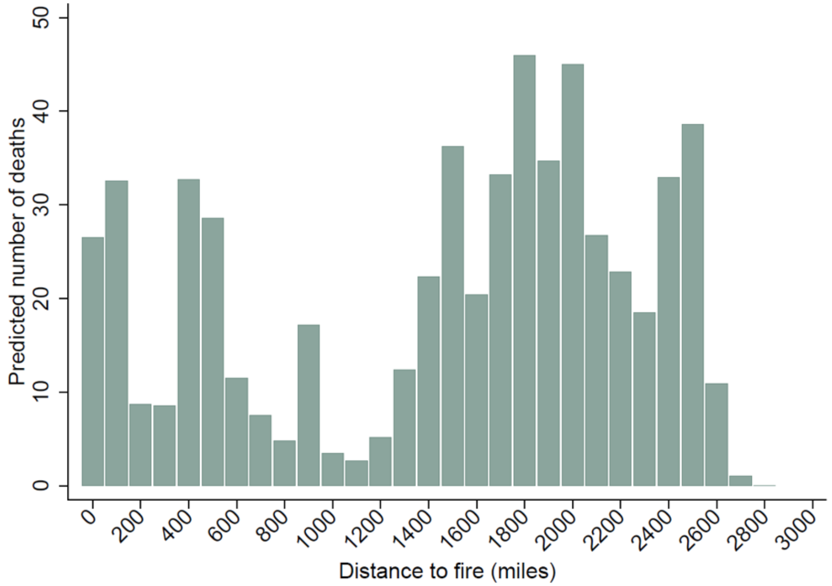
Source: Prediction is based on a 3-day mortality effect estimate of 1.2 deaths per million Medicare population per smoke day.

#1: Mendocino Complex Fire, 2018

Predicted smoke deaths = 592



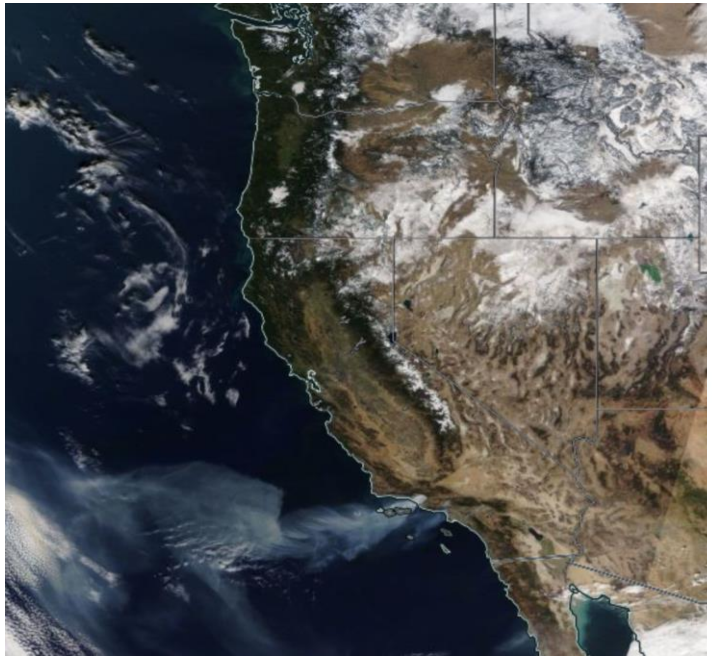


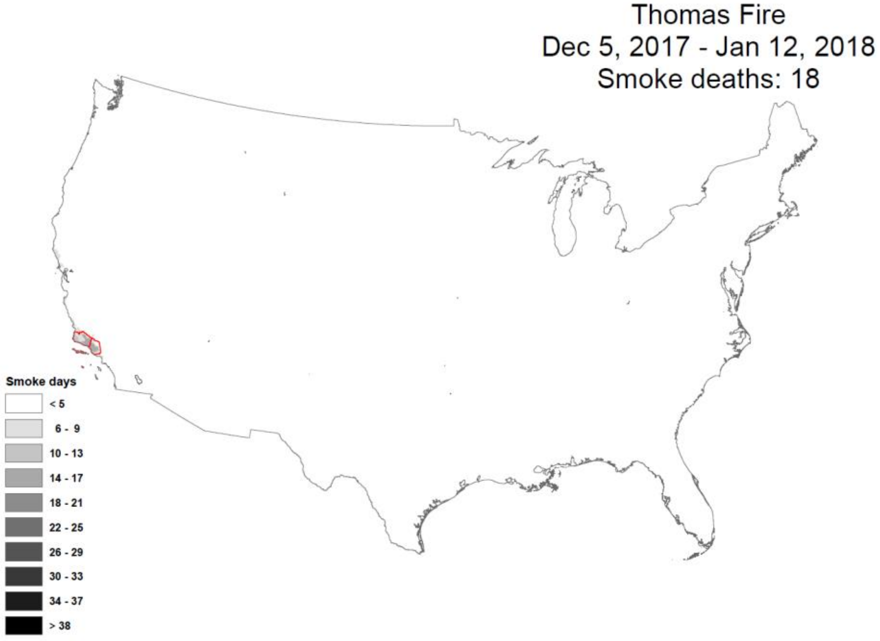


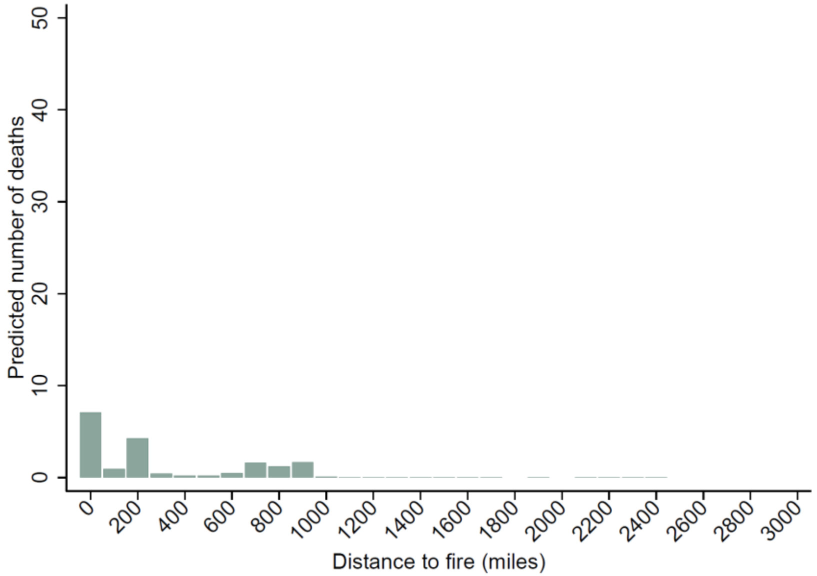
Source: Satellite imagery (left), days of smoke exposure (middle), predicted number of deaths due to smoke, by distance to fire (right).

#2: **Thomas Fire, 2017**

Predicted smoke deaths = 18



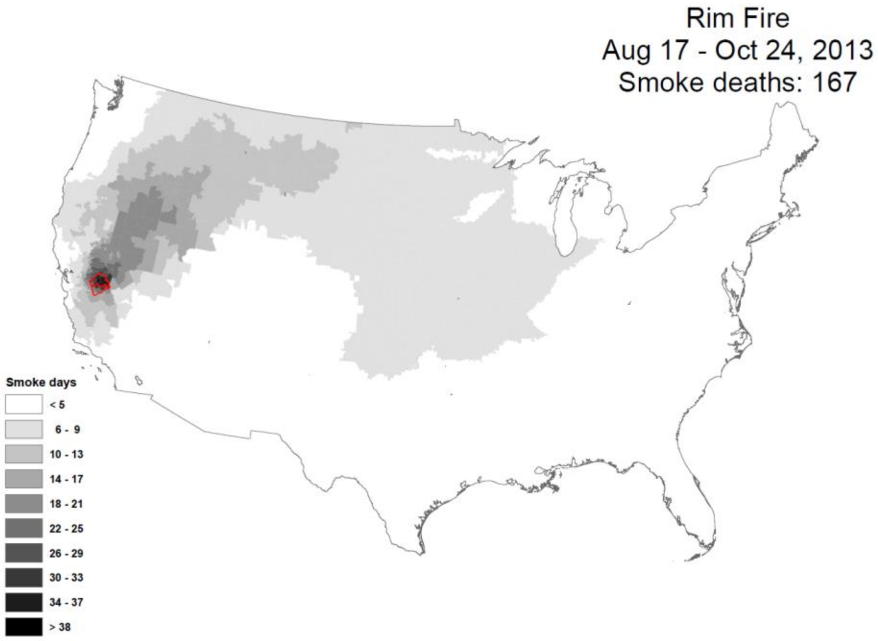


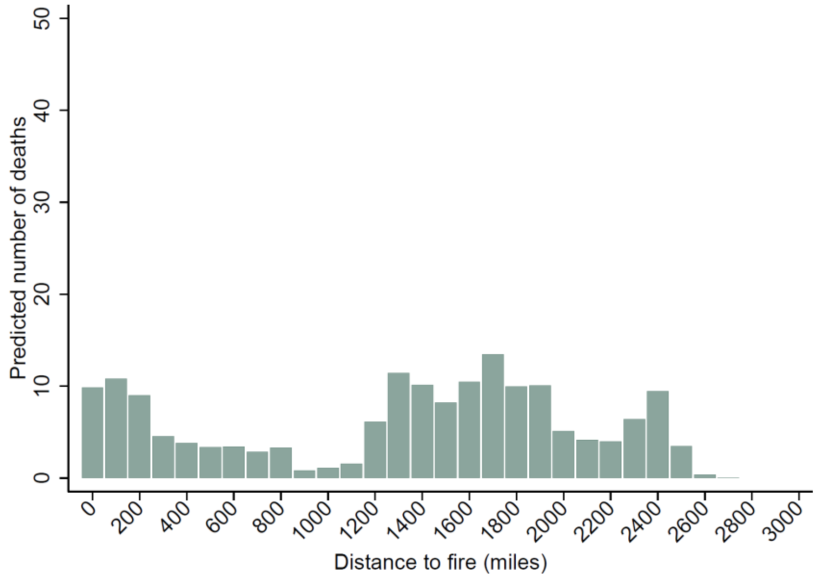


<u>Source:</u> Satellite imagery (left), days of smoke exposure (middle), predicted number of deaths due to smoke, by distance to fire (right).

#3: Rim Fire, 2013

Predicted smoke deaths = 167

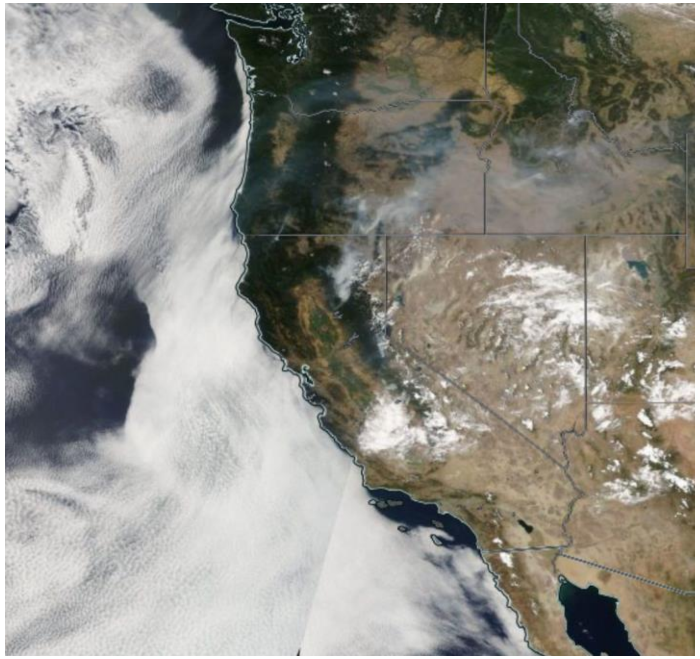


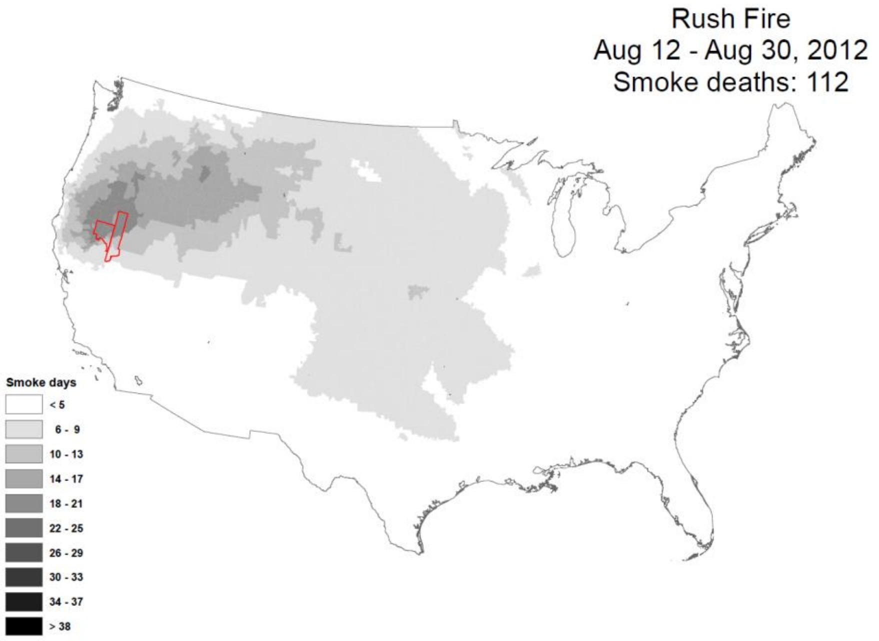


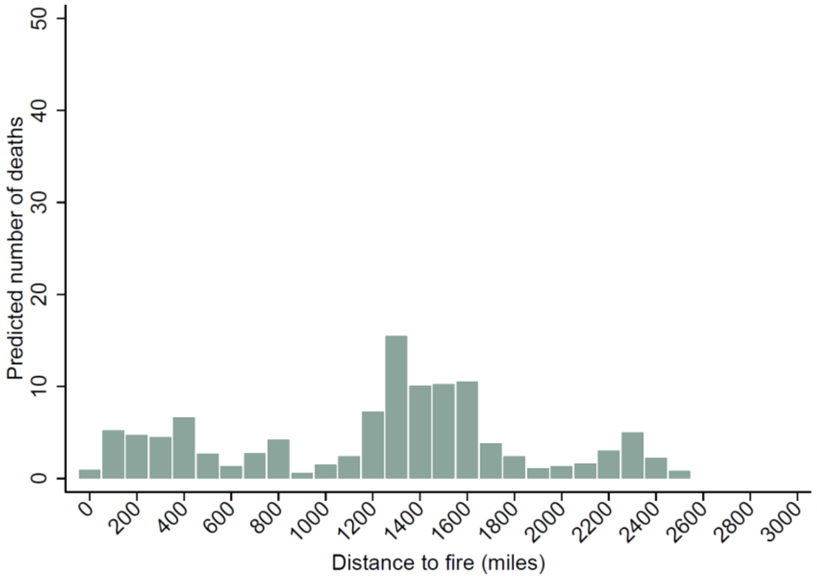
<u>Source:</u> Satellite imagery (left), days of smoke exposure (middle), predicted number of deaths due to smoke, by distance to fire (right).

#4: Rush Fire, 2012

Predicted smoke deaths = 112



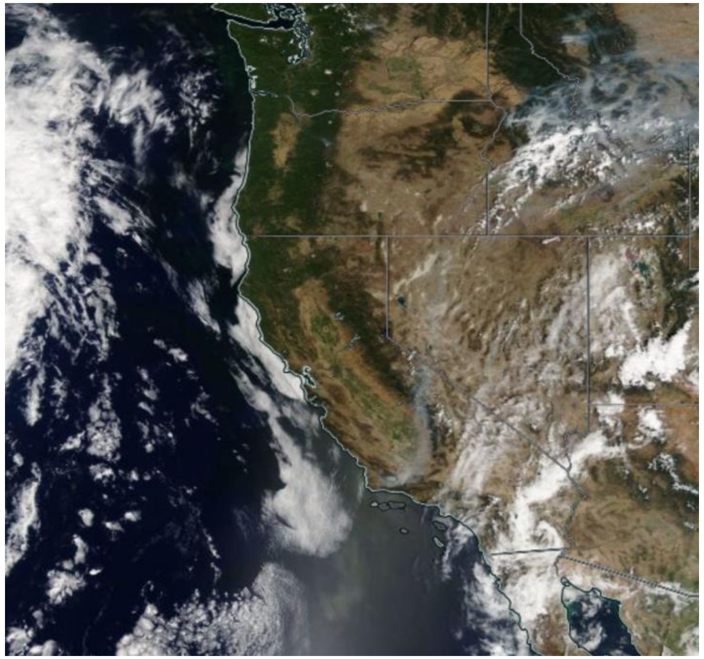


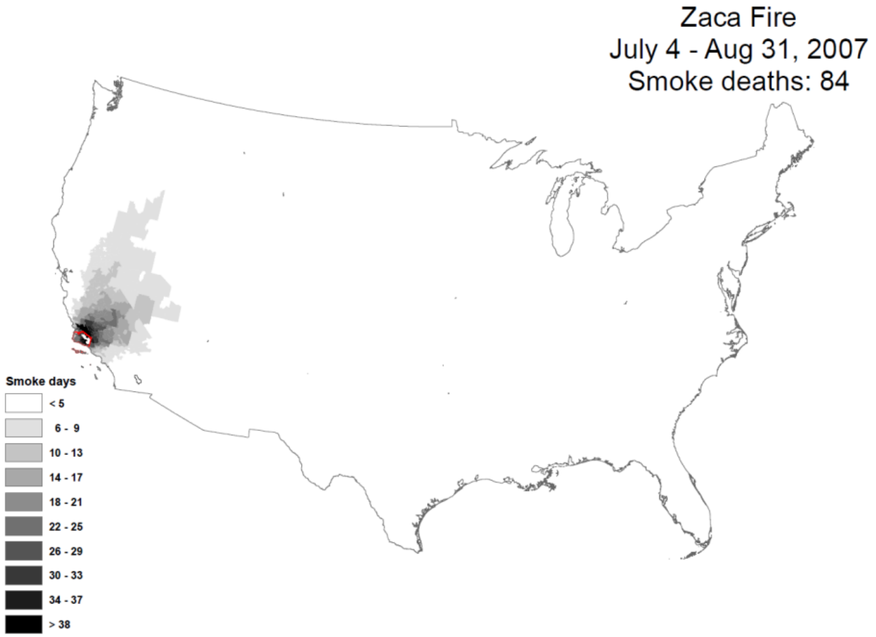


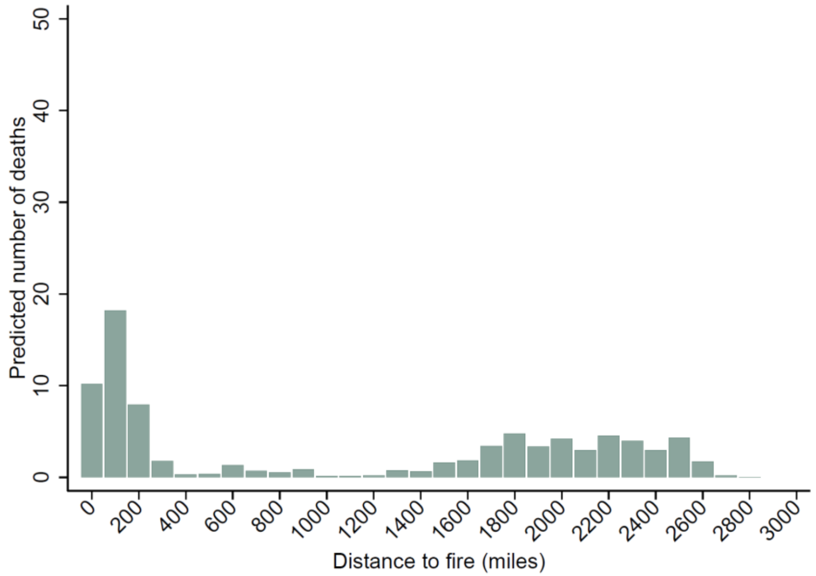
Source: Satellite imagery (left), days of smoke exposure (middle), predicted number of deaths due to smoke, by distance to fire (right).

#5: Zaca Fire, 2007

Predicted smoke deaths = 84







Source: Satellite imagery (left), days of smoke exposure (middle), predicted number of deaths due to smoke, by distance to fire (right).

Paper #2:
Air Pollution and the Labor Market: Evidence from Wildfire Smoke

September 2022

Mark Borgschulte (University of Illinois & IZA)
David Molitor (University of Illinois & NBER)
Eric Zou (University of Oregon & NBER)

Motivation

- Air pollution is a classic negative externality
  - Optimal regulation thought to trade off improvements in health against reductions in economic activity
  - Vast majority of costs thought to arise from direct health costs, esp. mortality and early-life impacts
  - i.e., Large costs concentrates in small groups

- Recent literature examines changes to labor markets
  - Improvements in labor market outcomes imply regulation may increase economic activity
  - Potential for small gains for much larger groups

Motivation

- Documented labor market channels:
  - Health and Avoidance Behavior: Moretti and Neidell (2011)
  - Labor Demand: Graff Zivin and Neidell (2009), Aldy and Bind (2014)
  - Labor Supply: Hanna and Oliva (2015), Aragon et al. (2016)
  - Productivity: Chang et al. (2016), Adhvaryu et al. (2016)

- Most studies isolate variation in unique settings, with large shocks and/or special populations to identify particular mechanisms

Primary Contributions

- This paper: Estimate impact of wildfire smoke on air quality and U.S. labor income and employment

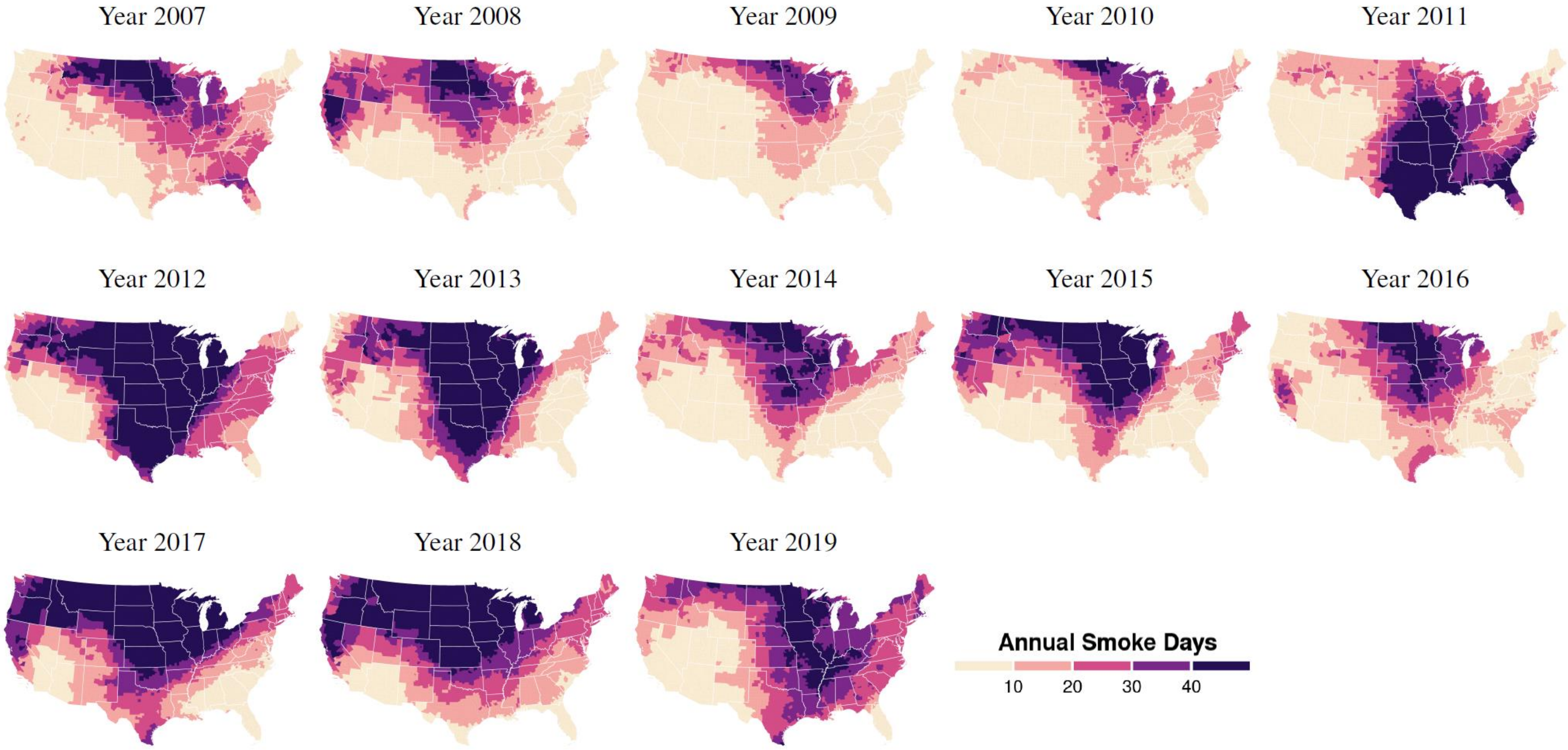
- Benchmark the welfare cost of lost earnings to the cost of premature mortality due to pollution

Labor Market Analysis

- Quarterly level analysis
  - Labor market outcomes are most commonly measured at the quarterly level
  - We aggregate daily smoke exposure (whether a county is exposed) to quarterly (how many days exposed)
  - We estimate the effect of smoke exposure on quarterly air quality and labor market outcomes

County Smoke Exposure: Days of Smoke Coverage by County 2007-2019

Midwest sees the most downwind smoke from California and Canada fires



<u>Notes:</u> This figure plots the number of days of smoke exposure in each county in the continental United States over the 2007-2019 sample period. Average population-weighted exposure during this period was 20.2 days per year.

Data

- Analysis is based on five main sets of publicly available data 2007-2019

1. Smoke
2. Air quality
3. Meteorology
4. Earnings and employment
5. Labor force participation

Data: Wildfire Smoke Plumes

- Hazard Mapping System (HMS) by NOAA (Ruminski et al., 2006)
  - https://satepsanone.nesdis.noaa.gov/pub/volcano/FIRE/HMS_ARCHIVE/
  - Daily polygon files that represent location of smoke plumes over North America
  - Data derived from the Geostationary Operational Environmental Satellite (GOES) visual bans (1-km) resolution and infrared bands (2-km resolution)
  - NOAA smoke analysts manually draw georeferenced polygons that represent the spatial extent of wildfire smoke plumes
  - Typically two drawings per day: once shortly before sunrise and once shortly after sunset

Data: Ground-level Air Quality

- Air Quality System (AQS) by U.S. EPA
  - https://aqs.epa.gov/aqsweb/airdata/download_files.html
  - Daily concentration of fine particulate matter (PM2.5), coarse particulate matter (PM10), ozone (O3), carbon monoxide (CO), nitrogen dioxide (NO2), and sulfur dioxide (SO2)
  - About 1,800 monitors; covers ~85% population
  - Compute county level pollution using inverse distance weighting (IDW): weighted average of all valid pollution readings from monitors that fall within 20 miles of a county's centroid, where the weights are the inverse of the distance between the monitor and the county centroid

Data: Weather Conditions

- Global Historical Climatology Network (GHCN) by the National Climatic Data Center
  - ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/daily/by_year
  - Station-daily temperature and precipitation readings

- North American Regional Reanalysis (NARR)
  - ftp://ftp.cdc.noaa.gov/Datasets/NARR/Dailies/monolevel
  - 32km grid-daily wind speed and direction

- We build control variables of weather conditions from these sources

Data: Labor Market Outcomes

- Quarterly Workforce Indicators (QWI) by U.S. Census Bureau
  - https://lehd.ces.census.gov/data/qwi/R2020Q4
  - Coverage: all workers except for members of the armed forces, self-employed, proprietors, and railroad employees
  - County-quarterly earnings and employment
  - Can also observe age groups and 2-digit NAICS industry breakouts

- Local Area Unemployment Statistics (LAUS) by U.S. Bureau of Labor Statistics
  - https://download.bls.gov/pub/time.series/la
  - County-monthly LFP counts, which we average to the quarterly frequency to match QWI

Regression Analysis

- Pollution regression:

$$[PM_{2.5}]_{cq} = \beta \cdot SmokeDay_{cq} + \alpha_{c\times quarter-of-year} + \alpha_{state\times year} + \epsilon_{cq}$$

  - $[PM_{2.5}]_{cq}$ = average $PM_{2.5}$ concentration in county c quarter q
  - $SmokeDay_{cq}$ = number of days in the quarter county is covered by smoke
  - $\alpha_{c\times quarter-of-year}$, $\alpha_{state\times year}$ = county × quarter-of-year FEs, state × year FEs

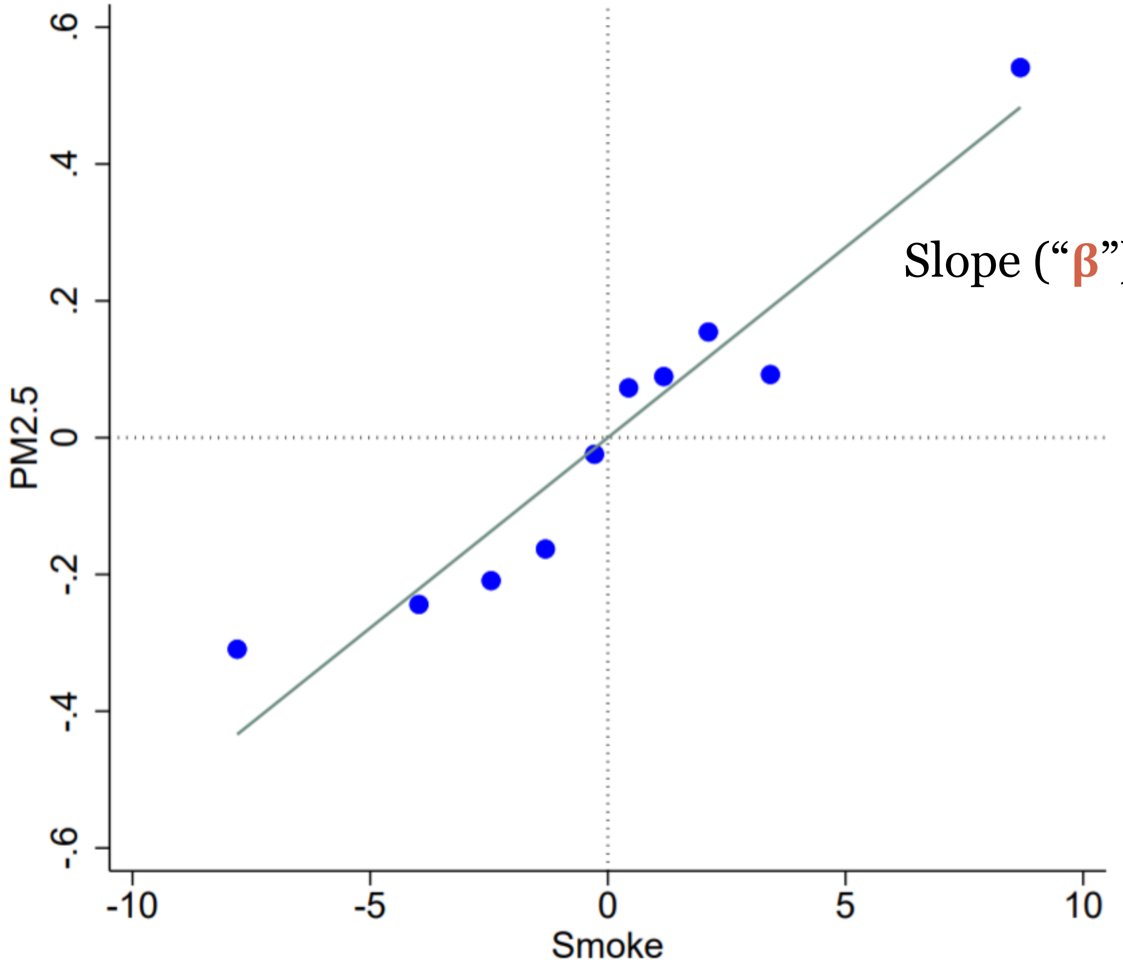
  - Source of variation: within county × quarter-of-year, across different years

    Ex: Summer in Orange county, 2015 vs. 2016

  - Two-way cluster SEs at the county and the state × quarter levels

Quarterly Pollution Effect: PM2.5 vs Smoke Days

Binscatter conditioned on county-quarter FEs, state-year FEs



Slope ("β") = 0.056***
(0.007)

Notes: Decile binscatter of FE residualized PM2.5 against FE residualized smoke. Slope of linear fit represents the OLS estimate.

Regression Analysis

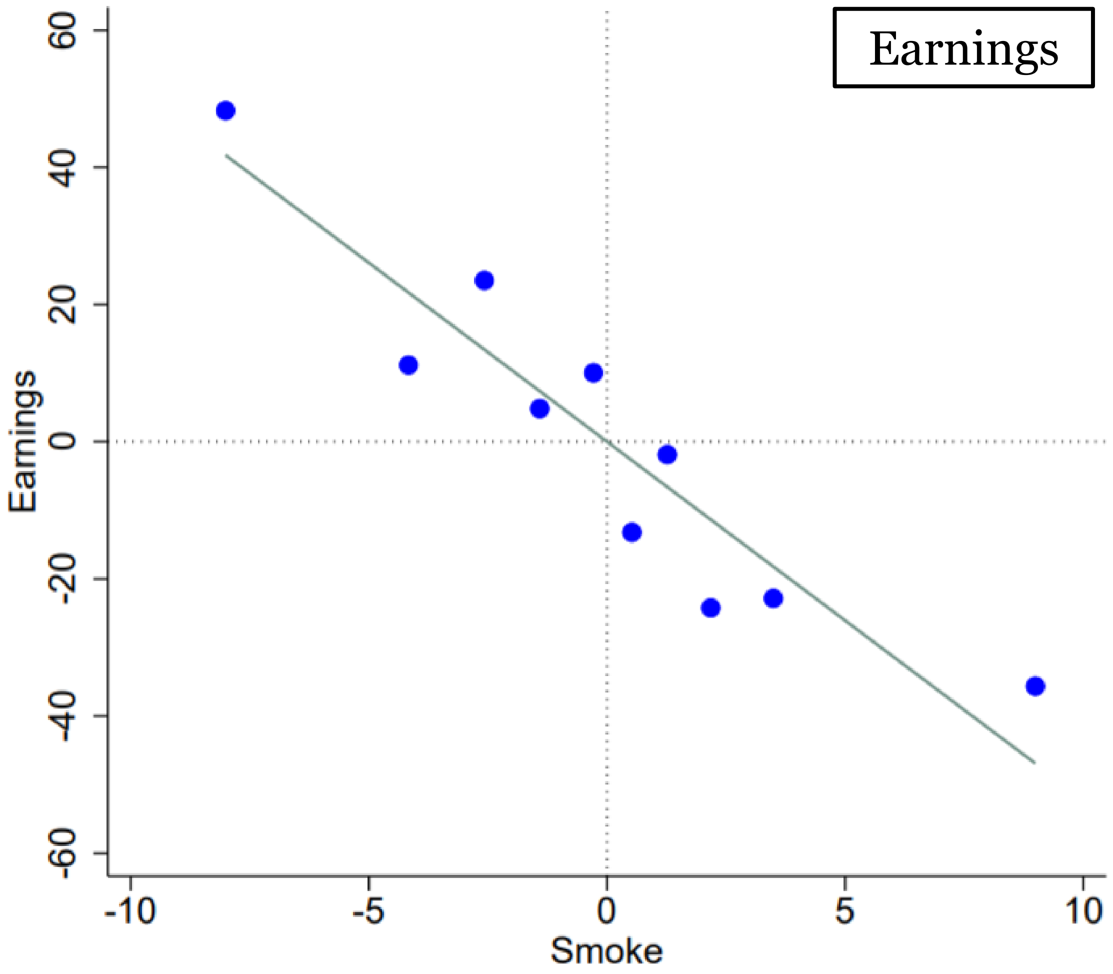
- Labor market outcomes regression:

$$\Delta \mathrm{Y}_{cq} = \beta \cdot \mathrm{SmokeDay}_{cq} + \alpha_{c\times quarter-of-year} + \alpha_{state\times year} + \varepsilon_{cq}$$

  - $\Delta \mathrm{Y}_{cq}$ = Change in labor market outcomes in county c quarter q from the same quarter-of-year in the previous year
    - Per capita earnings
    - Employment per million people aged 16+
    - Labor force participation per million people

Labor Market Effect: Earnings vs Smoke Days

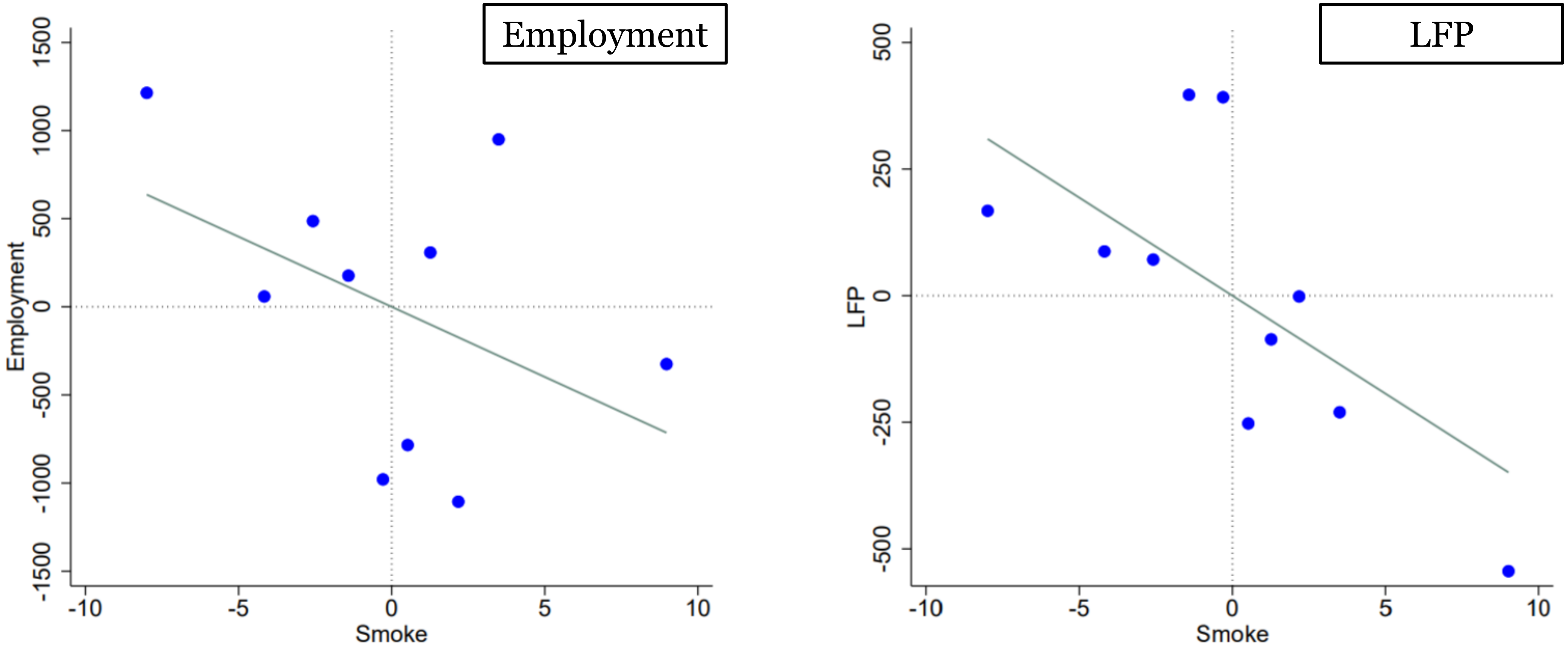
Binscatter conditioned on county-quarter FEs, state-year FEs



Notes: Decile binscatter of FE residualized outcome against FE residualized smoke. Slope of linear fit represents the OLS estimate.

Labor Market Effect: Employment and LFP vs Smoke Days

Binscatter conditioned on county-quarter FEs, state-year FEs



Notes: Decile binscatter of FE residualized outcome against FE residualized smoke. Slope of linear fit represents the OLS estimate.

Main regression: The effect of wildfire smoke

More smoke days leads to worse pollution and labor market outcomes

	(1)	(2)	(3)	(4)
	$PM_{2.5}$	earnings	employment	LFP
A. First-stage and reduced-form estimates				
Smoke	0.056***	-5.217***	-79.6***	-38.7***
	(0.007)	(0.776)	(21.9)	(9.2)
Outcome mean	9.46	5,359.7	625,776	625,434
Observations	75,207	160,346	160,346	161,498

- One more day of smoke exposure in the quarter increases quarterly average PM2.5 by 0.056 ug/m3
- Implies that wildfire smoke accounts for 23% of ambient PM2.5
- Complements EPA National Emissions Inventory estimates that wildfires produced 18% of PM2.5 emissions in 2007–2017

Notes: Each column reports a separate regression of an outcome on quarterly smoke exposure days.

Main regression: The effect of wildfire smoke

More smoke days leads to worse pollution and labor market outcomes

	(1)	(2)	(3)	(4)
	$PM_{2.5}$	earnings	employment	LFP
A. First-stage and reduced-form estimates				
Smoke	0.056***	-5.217***	-79.6***	-38.7***
	(0.007)	(0.776)	(21.9)	(9.2)
Outcome mean	9.46	5,359.7	625,776	625,434
Observations	75,207	160,346	160,346	161,498

- One more day of smoke exposure in the quarter reduces quarterly per capital earnings by $5.2 (or a 0.1% reduction)
- Implies that wildfire smoke accounts for a national annual loss of $125.4 billion in earnings (or a 2% reduction)

Notes: Each column reports a separate regression of an outcome on quarterly smoke exposure days.

Main regression: The effect of wildfire smoke

More smoke days leads to worse pollution and labor market outcomes

	(1)	(2)	(3)	(4)
	$PM_{2.5}$	earnings	employment	LFP
A. First-stage and reduced-form estimates				
Smoke	0.056***	-5.217***	-79.6***	-38.7***
	(0.007)	(0.776)	(21.9)	(9.2)
Outcome mean	9.46	5,359.7	625,776	625,434
Observations	75,207	160,346	160,346	161,498

- Smoke also triggers extensive margin responses:
- Reduction in employment by 80 per million people (or a 0.013% reduction) and LFP by 39 per million people (or a 0.006% reduction)
- Assuming those who lost employment earn average incomes, the employment reductions can account for 13% of the total earnings effect of smoke exposure

Notes: Each column reports a separate regression of an outcome on quarterly smoke exposure days.

Robustness

- Paper includes a host of sensitivity checks
  - Alternative smoke definitions: fraction of county covered by smoke
  - Alternative fixed effects controls: e.g. Census Regions-by-year fixed effects
  - Alternative outcome specifications: e.g. no first-differenced outcome
  - Alternative standard errors clustering: e.g. cluster by state

- Here, present dynamic specifications that augment the main estimation equation with leads and lags of smoke exposure
  - Lagged smoke exposure describe whether the effects of smoke persist after the year of exposure
  - Lead smoke exposure provide a "placebo" check on the effect of next year's smoke on this year's pollution and labor market responses

Dynamic Specification

- **Pollution regression:**

$$[PM_{2.5}]_{cq} = \beta \cdot \text{SmokeDay}_{cq}$$
$$+\alpha_{c\times \text{quarter-of-year}} + \alpha_{\text{state}\times\text{year}} + \epsilon_{cq}$$

- **Labor market regression:**

$$\Delta Y_{cq} = \beta \cdot \text{SmokeDay}_{cq}$$
$$+ \alpha_{c\times \text{quarter-of-year}} + \alpha_{\text{state}\times\text{year}} + \epsilon_{cq}$$

Dynamic Specification

- <u>Pollution regression:</u>

$$[PM_{2.5}]_{cq} = \beta \cdot SmokeDay_{cq} + \sum_{\tau=+1,+2} \beta_\tau \cdot SmokeDay_{cq(y+\tau)} + \sum_{\tau=-1,-2} \beta_\tau \cdot SmokeDay_{cq(y+\tau)}$$
$$+\alpha_{c\times quarter-of-year} + \alpha_{state\times year} + \epsilon_{cq}$$

- <u>Labor market regression:</u>

$$\Delta Y_{cq} = \beta \cdot SmokeDay_{cq} + \sum_{\tau=+1,+2} \beta_\tau \cdot SmokeDay_{cq(y+\tau)} + \sum_{\tau=-1,-2} \beta_\tau \cdot SmokeDay_{cq(y+\tau)}$$
$$+ \alpha_{c\times quarter-of-year} + \alpha_{state\times year} + \epsilon_{cq}$$

Dynamic Specification

- <u>Pollution regression:</u>

$$[PM_{2.5}]_{cq} = \beta \cdot \text{SmokeDay}_{cq} \boxed{+ \sum_{\tau=+1,+2} \beta_\tau \cdot \text{SmokeDay}_{cq(y+\tau)}} + \sum_{\tau=-1,-2} \beta_\tau \cdot \text{SmokeDay}_{cq(y+\tau)}$$
$$+\alpha_{c\times \text{quarter-of-year}} + \alpha_{\text{state}\times\text{year}} + \epsilon_{cq}$$

Effect of next years' smoke ("Placebo")

- <u>Labor market regression:</u>

$$\Delta Y_{cq} = \beta \cdot \text{SmokeDay}_{cq} \boxed{+ \sum_{\tau=+1,+2} \beta_\tau \cdot \text{SmokeDay}_{cq(y+\tau)}} + \sum_{\tau=-1,-2} \beta_\tau \cdot \text{SmokeDay}_{cq(y+\tau)}$$
$$+ \alpha_{c\times \text{quarter-of-year}} + \alpha_{\text{state}\times\text{year}} + \epsilon_{cq}$$

Dynamic Specification

- Pollution regression:

$$[PM_{2.5}]_{cq} = \beta \cdot \text{SmokeDay}_{cq} + \sum_{\tau=+1,+2} \beta_\tau \cdot \text{SmokeDay}_{cq(y+\tau)} \boxed{+ \sum_{\tau=-1,-2} \beta_\tau \cdot \text{SmokeDay}_{cq(y+\tau)}}$$
$$+\alpha_{c\times \text{quarter-of-year}} + \alpha_{\text{state}\times\text{year}} + \epsilon_{cq}$$

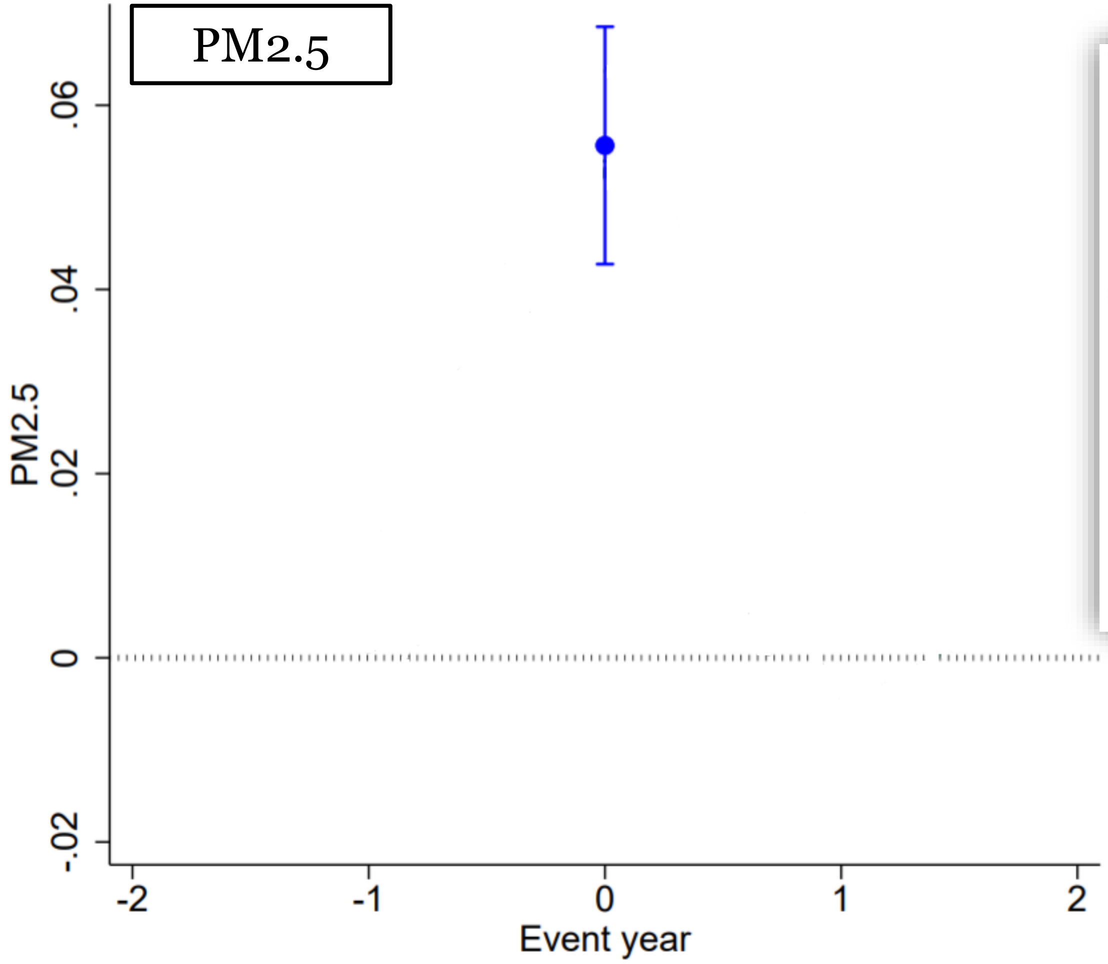
Effect of previous years' smoke (lagged effects)

- Labor market regression:

$$\Delta Y_{cq} = \beta \cdot \text{SmokeDay}_{cq} + \sum_{\tau=+1,+2} \beta_\tau \cdot \text{SmokeDay}_{cq(y+\tau)} \boxed{+ \sum_{\tau=-1,-2} \beta_\tau \cdot \text{SmokeDay}_{cq(y+\tau)}}$$
$$+ \alpha_{c\times \text{quarter-of-year}} + \alpha_{\text{state}\times\text{year}} + \epsilon_{cq}$$

Dynamic specification: Impact of previous and *next* years' smoke

Smoke mostly leads to contemporaneous impacts

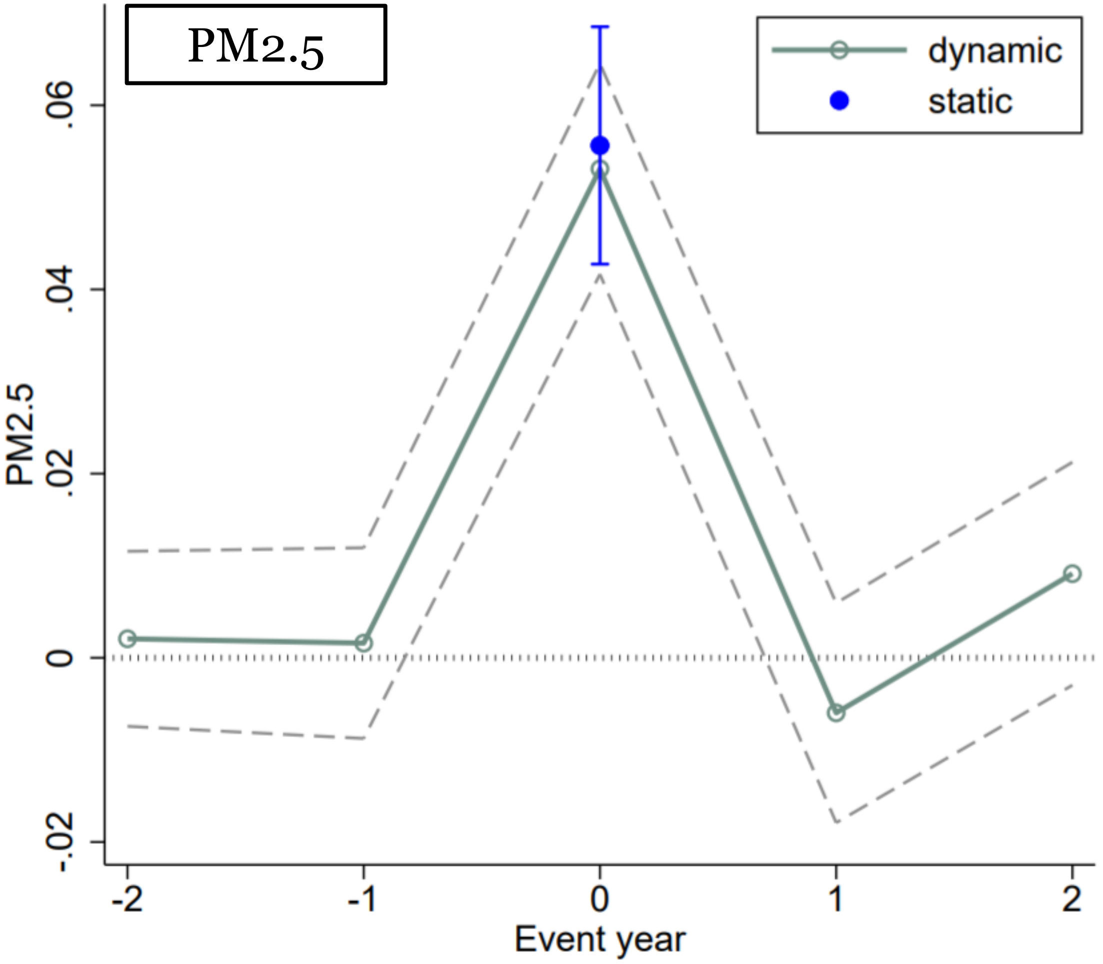


	(1) PM$_{2.5}$	(2) earnings	(3) employment	(4) LFP
A. First-stage and reduced-form estimates				
Smoke	0.056***	-5.217***	-79.6***	-38.7***
	(0.007)	(0.776)	(21.9)	(9.2)
Outcome mean	9.46	5,359.7	625,776	625,434
Observations	75,207	160,346	160,346	161,498

Notes: Augmented regression with two lead (negative event years) and two lag terms (positive event years) of smoke exposure. The "static" estimate with no leads lags terms is superimposed for comparison. Dashed lines and range bar show 95% CI.

Dynamic specification: Impact of previous and *next* years' smoke

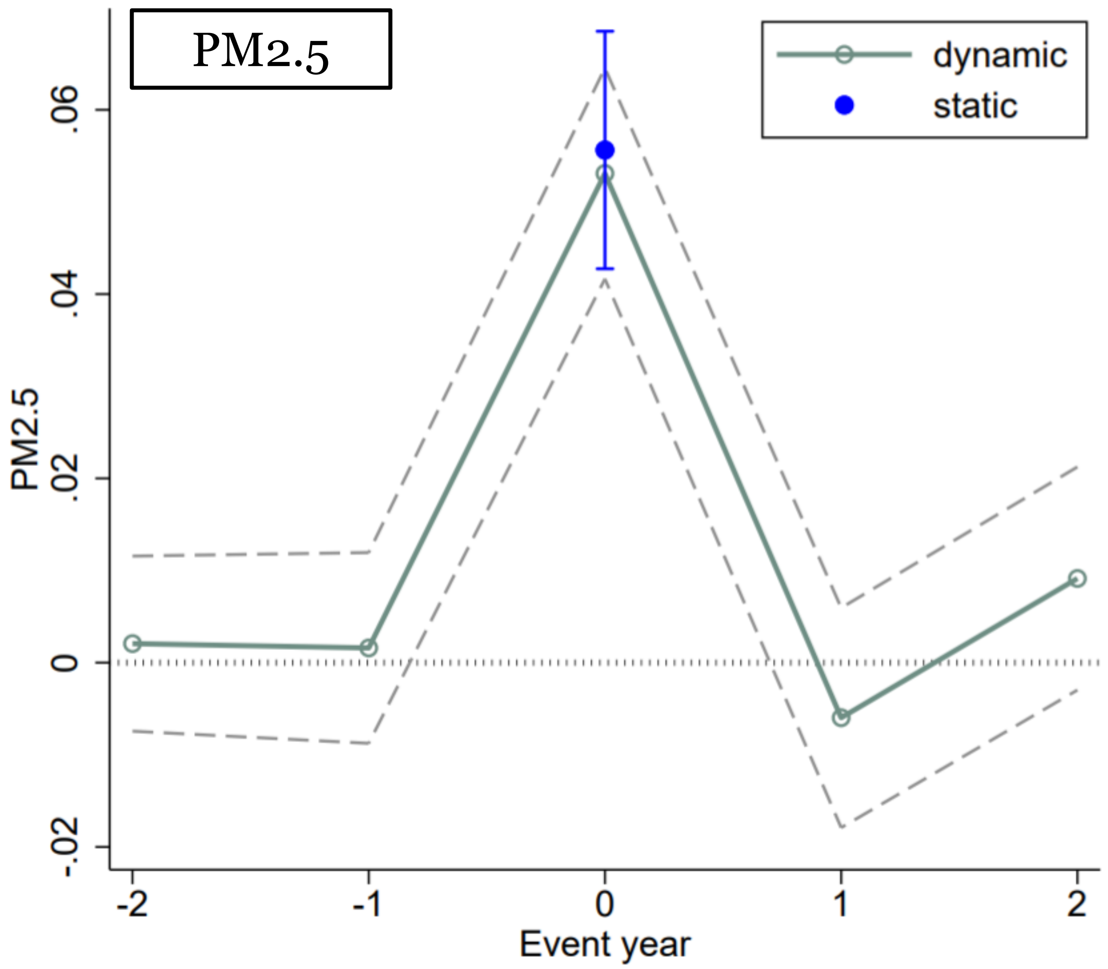
Smoke mostly leads to contemporaneous impacts

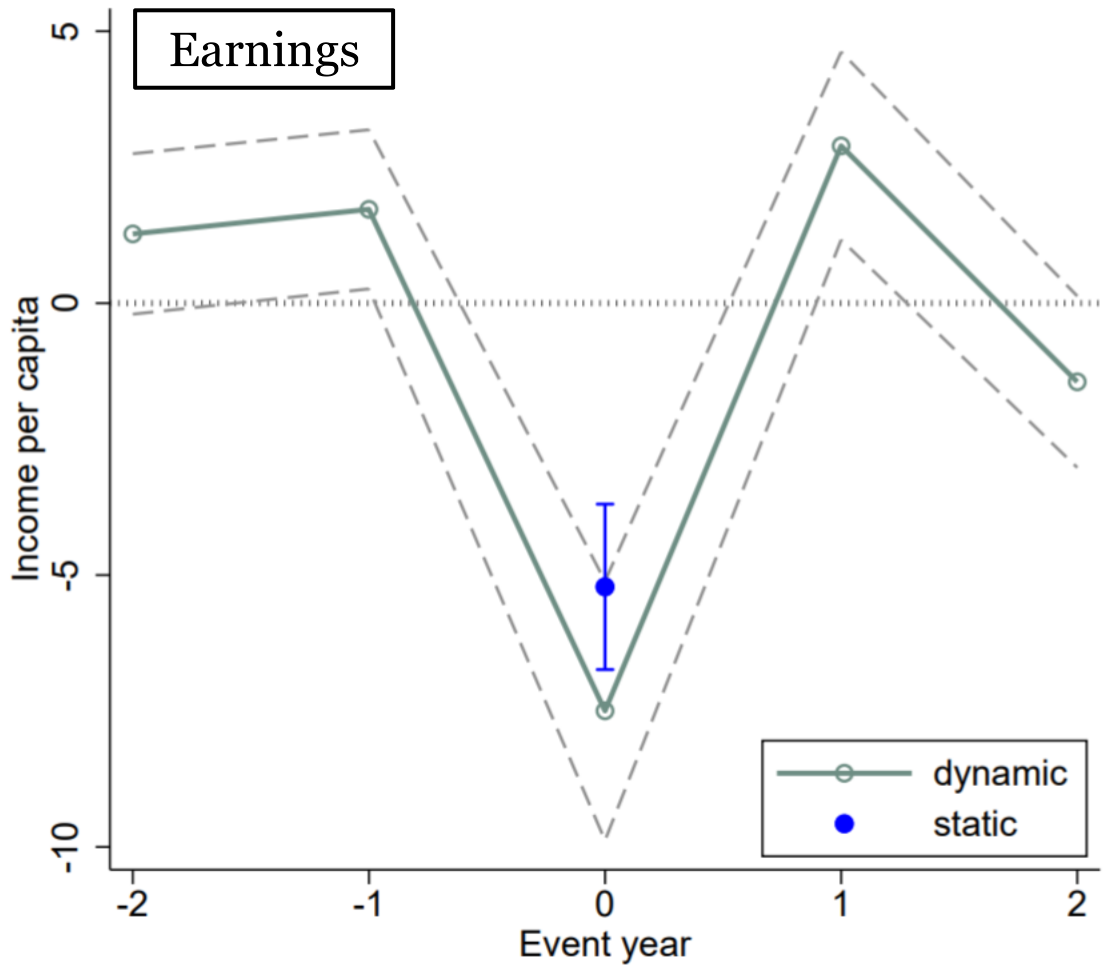


Notes: Augmented regression with two lead (negative event years) and two lag terms (positive event years) of smoke exposure. The "static" estimate with no leads lags terms is superimposed for comparison. Dashed lines and range bar show 95% CI.

Dynamic specification: Impact of previous and *next* years' smoke

Smoke mostly leads to contemporaneous impacts

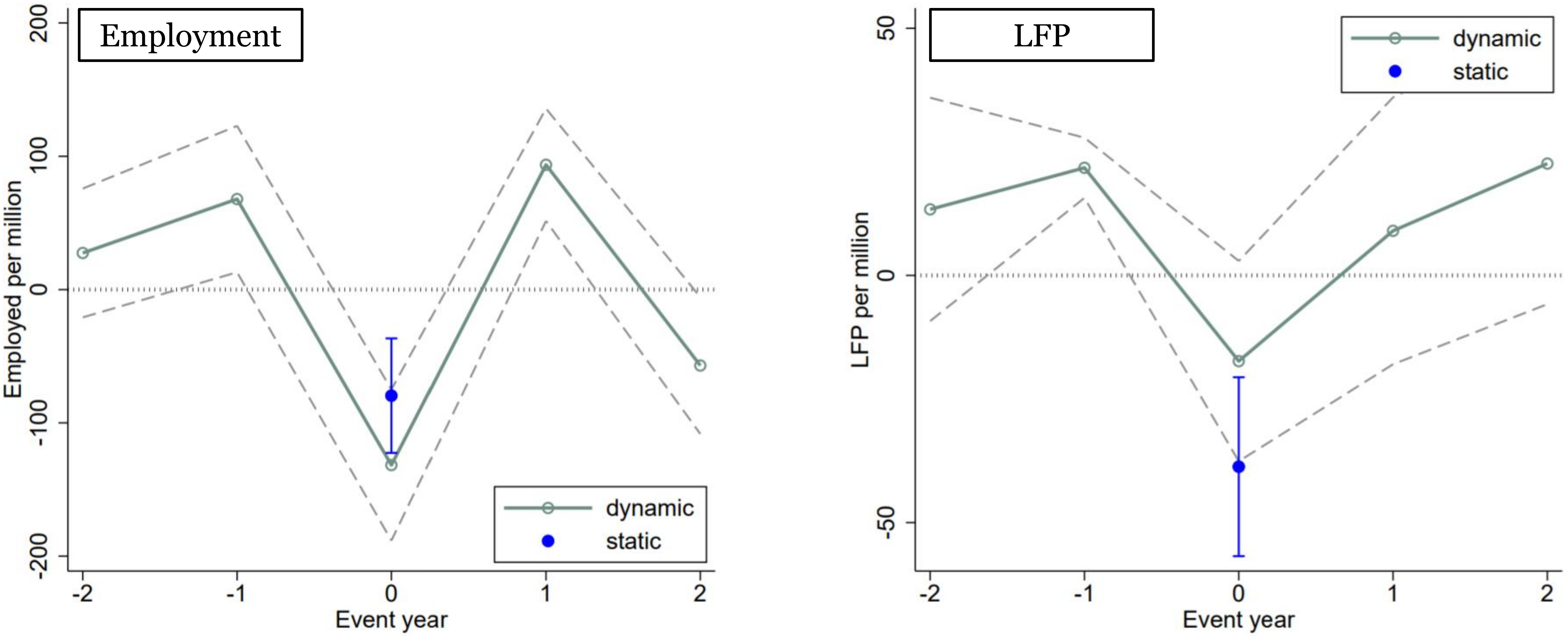




Notes: Augmented regression with two lead (negative event years) and two lag terms (positive event years) of smoke exposure. The "static" estimate with no leads lags terms is superimposed for comparison. Dashed lines and range bar show 95% CI.

Dynamic specification: Impact of previous and *next* years' smoke

Smoke mostly leads to contemporaneous impacts



Notes: Augmented regression with two lead (negative event years) and two lag terms (positive event years) of smoke exposure. The "static" estimate with no leads lags terms is superimposed for comparison. Dashed lines and range bar show 95% CI.

Instrumental Variable (IV) Analysis

- Drifting wildfire smoke provides a natural context to estimate the causal effect of air pollution on labor market outcomes using an instrumental variables (IV) framework
  - Easier to benchmark against prior studies on the effect of pollution
  - Relevant for policy

Instrumental Variable (IV) Analysis

- Pollution regression:

$$[\mathrm{PM}_{2.5}]_{cq} = \beta \cdot \mathrm{SmokeDay}_{cq} + \alpha_{c \times quarter-of-year} + \alpha_{state \times year} + \epsilon_{cq}$$

- Labor market outcomes regression:

$$\Delta Y_{cq} = \beta \cdot \mathrm{SmokeDay}_{cq} + \alpha_{c \times quarter-of-year} + \alpha_{state \times year} + \varepsilon_{cq}$$

Instrumental Variable (IV) Analysis

- First stage regression:

$$[PM_{2.5}]_{cq} = \beta \cdot \text{SmokeDay}_{cq} + \alpha_{c\times \text{quarter}-\text{of}-\text{year}} + \alpha_{\text{state}\times\text{year}} + \epsilon_{cq}$$

- Reduced form regression:

$$\Delta Y_{cq} = \beta \cdot \text{SmokeDay}_{cq} + \alpha_{c\times \text{quarter}-\text{of}-\text{year}} + \alpha_{\text{state}\times\text{year}} + \varepsilon_{cq}$$

- Two-stage least squares:

$$\Delta Y_{cq} = \theta \cdot [P\widehat{M}_{2.5}]_{cq} + \alpha_{c\times \text{quarter}-\text{of}-\text{year}} + \alpha_{\text{state}\times\text{year}} + e_{cq}$$

  - Just-identified IV model with one excluded instrument (SmokeDay_{cq})
  - First stage: smoke strongly predicts PM2.5
  - Exclusion restriction: smoke effects labor market outcomes ONLY through PM2.5

IV Estimates: The Effect of PM2.5 on Earnings, Employment, and LFP

Just-identified IV model with smoke days as the instrument for PM2.5

	(1)	(2)	(3)	(4)
	$PM_{2.5}$	earnings	employment	LFP
B. OLS estimates				
$PM_{2.5}$	–	-10.566***	-261.0**	-95.7*
	–	(3.089)	(113.9)	(54.7)
Outcome mean	–	5,687.6	643,597	631,806
Observations	–	74,725	74,725	75,193
C. IV estimates				
$\hat{PM}_{2.5}$	–	-103.1***	-1750.1***	-790.9***
	–	(20.4)	(434.8)	(182.1)
Kleibergen-Paap F	–	71.8	71.2	71.7
Outcome mean	–	5,687.6	643,597	631,806
Observations	–	74,725	74,725	75,193

Notes: Each column-panel reports a separate regression of an outcome on quarterly PM2.5.

IV Estimates: The Effect of PM2.5 on Earnings, Employment, and LFP

Just-identified IV model with smoke days as the instrument for PM2.5

	(1)	(2)	(3)	(4)
	$PM_{2.5}$	earnings	employment	LFP
B. OLS estimates				
$PM_{2.5}$	–	-10.566***	-261.0**	-95.7*
	–	(3.089)	(113.9)	(54.7)
Outcome mean	–	5,687.6	643,597	631,806
Observations	–	74,725	74,725	75,193
C. IV estimates				
$\hat{PM}_{2.5}$	–	-103.1***	-1750.1***	-790.9***
	–	(20.4)	(434.8)	(182.1)
Kleibergen-Paap F	–	71.8	71.2	71.7
Outcome mean	–	5,687.6	643,597	631,806
Observations	–	74,725	74,725	75,193

- Can detect PM2.5 effects using simple OLS, but estimates are an order of magnitude smaller than IV

Notes: Each column-panel reports a separate regression of an outcome on quarterly PM2.5.

IV Estimates: The Effect of PM2.5 on Earnings, Employment, and LFP

Just-identified IV model with smoke days as the instrument for PM2.5

	(1)	(2)	(3)	(4)
	$PM_{2.5}$	earnings	employment	LFP
B. OLS estimates				
$PM_{2.5}$	–	-10.566***	-261.0**	-95.7*
	–	(3.089)	(113.9)	(54.7)
Outcome mean	–	5,687.6	643,597	631,806
Observations	–	74,725	74,725	75,193
C. IV estimates				
$\hat{PM}_{2.5}$	–	-103.1***	-1750.1***	-790.9***
	–	(20.4)	(434.8)	(182.1)
Kleibergen-Paap F	–	71.8	71.2	71.7
Outcome mean	–	5,687.6	643,597	631,806
Observations	–	74,725	74,725	75,193

- Headline number : a 1-ug/m3 increase in quarterly PM2.5 reduces quarterly per capita earnings by $103
- Translate to an Earnings-PM2.5 elasticity of -0.18

Notes: Each column-panel reports a separate regression of an outcome on quarterly PM2.5.

Two Discussion Points

- Threats to the IV’s exclusion restriction assumption
- Credibility of effect size

Threats to the Exclusion Restriction

- IV assumes the effect of smoke on labor market outcomes operate entirely through PM2.5 changes
- Two potential threats to this assumption

1. Smoke may interact with local atmospheric conditions, such as air temperature and precipitation which can have independent impacts on worker productivity
2. Wildfire smoke contains a complex mix of air pollutants, not just PM2.5

Threats to the Exclusion Restriction

- IV assumes the effect of smoke on labor market outcomes operate entirely through PM2.5 changes
- Two potential threats to this assumption

1. Smoke may interact with local atmospheric conditions, such as air temperature and precipitation which can have independent impacts on worker productivity
   - We find that controlling flexibly for weather variables, including bins of air temperature, precipitation, wind direction, and wind speed, has little impact on our smoke effect estimates

		(1) earnings	(2) employment	(3) lfp
B. Weather controls				
Temp. Ppt. Wdir. Wspd.	F=45.9	-124.074***	-2065.7***	-814.8***
		(28.967)	(544.2)	(231.5)
Wdirx × state	F=56.0	-113.794***	-1643.9***	-758.3***
		(25.824)	(453.2)	(199.7)
Wdirx × county	F=50.0	-123.416***	-1768.0***	-778.0***
		(29.247)	(513.3)	(226.9)

2. Wildfire smoke contains a complex mix of air pollutants, not just PM2.5

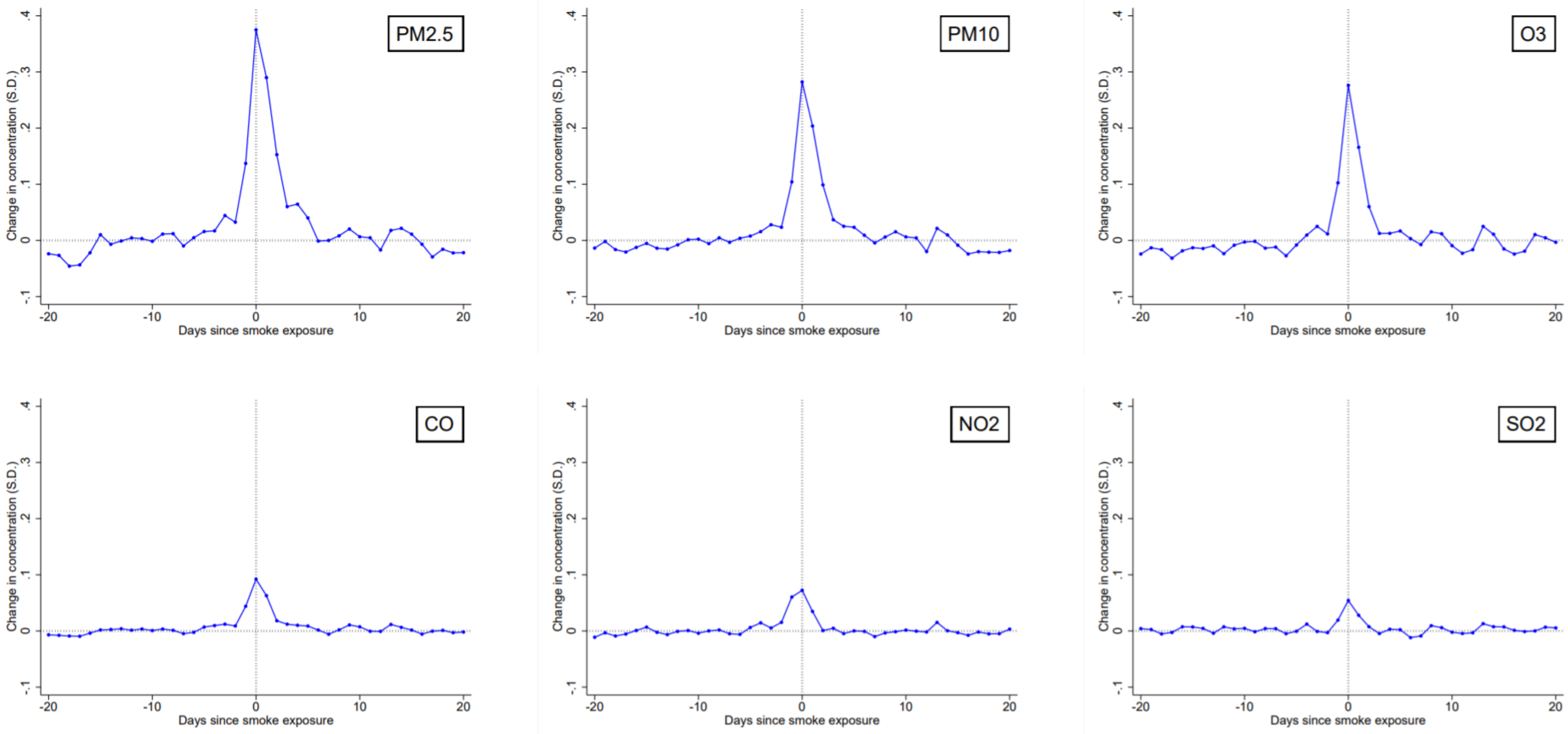
Threats to the Exclusion Restriction

- IV assumes the effect of smoke on labor market outcomes operate entirely through PM2.5 changes
- Two potential threats to this assumption

1. Smoke may interact with local atmospheric conditions, such as air temperature and precipitation which can have independent impacts on worker productivity
2. Wildfire smoke contains a complex mix of air pollutants, not just PM2.5
   - Cannot address directly as we only have one instrument; difficult to find quasi-experimental variation of one pollutant while holding all other pollutants constant
   - We report response of all six EPA criteria pollutants
   - Multivariate OLS suggests PM2.5 seems to be the most important predictor
   - Preferred interpretation of our estimates: the impact of bad air quality as proxied by PM2.5 concentration

Event Study: Changes in Criteria Pollutants by Days since Smoke Exposure

Smoke generates the largest spikes in PM and O3



Notes: Each panel shows coefficients from a regression of daily standardized (mean 0, sd 1) pollutant concentration on indicators of daily smoke exposure up to 20 days before and after the day of observation.

Multivariate OLS: **Earnings and Criteria Air Pollutants**

Statistically, PM2.5 seems to be the most robust predictor for earnings among criteria pollutants

	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	-10.6***	-13.6***	-11.1***	-14.1***	-10.0**	-15.4***
	(3.1)	(3.5)	(3.4)	(4.4)	(4.0)	(5.1)
PM_{10}	-	1.9*	-	-	-	2.6*
	-	(1.1)	-	-	-	(1.4)
O_3	-	-	-1.2	-	-	-2.5
	-	-	(1.1)	-	-	(1.7)
SO_2	-	-	-	-3.6	-	-7.6*
	-	-	-	(2.3)	-	(4.5)
NO_2	-	-	-	-	-5.5	-4.2
	-	-	-	-	(3.9)	(3.6)
Outcome mean	5,687.6	5,975.2	5,763.9	6,114.5	6,211.8	6,390.4
Observations	74,725	42,616	64,248	40,363	31,534	23,373

Notes: Each column reports a separate regression. Pollutants are measured in µg/m3 (PM2.5 and PM10), ppb (O3), and ppm (SO2 and NO2).

Effect Size

- Compare our IV estimates to prior studies of the effect of pollution on labor market outcomes

- Difficult to do because studies differ substantially in research design and context
  - Country, time periods, industry focus, measures of labor market outcome, the type of pollutant examined, and background pollution level, etc.

- We make a simplifying choice and conduct comparisons using a measure of "pollution elasticity"
  - The percentage change in a labor market outcome per one percent change in the level of pollution being studied

Effect Size

- We find an implied earnings-PM2.5 elasticity of -0.18
- This magnitude is in line with the recent quasi-experimental literature on the effect of pollution on labor market outcomes

Graff Zivin and Neidell (2012):	-0.26
Chang et al. (2016):	-0.062
Chang et al. (2019):	-0.023
Adhvaryu, Kala, and Nyshadham (2022):	-0.052
He, Liu, and Salvo (2018):	-0.30
Aragon, Miranda, and Oliva (2017):	-0.20
Hanna and Oliva (2015):	-0.15
Fu, Viard, and Zhang (2021):	-0.44
Isen, Rossin-Slater, and Walker (2017):	-0.10
Average:	-0.18

Heterogeneity

- National coverage allows us to examine important heterogeneity in the impact of pollution
  - By characteristics of the neighborhood
  - By age groups
  - By industry sectors
- Descriptive & not theory driven. But hopefully illuminates future studies on mechanisms

Heterogeneity: Effects of smoke by neighborhood characteristics

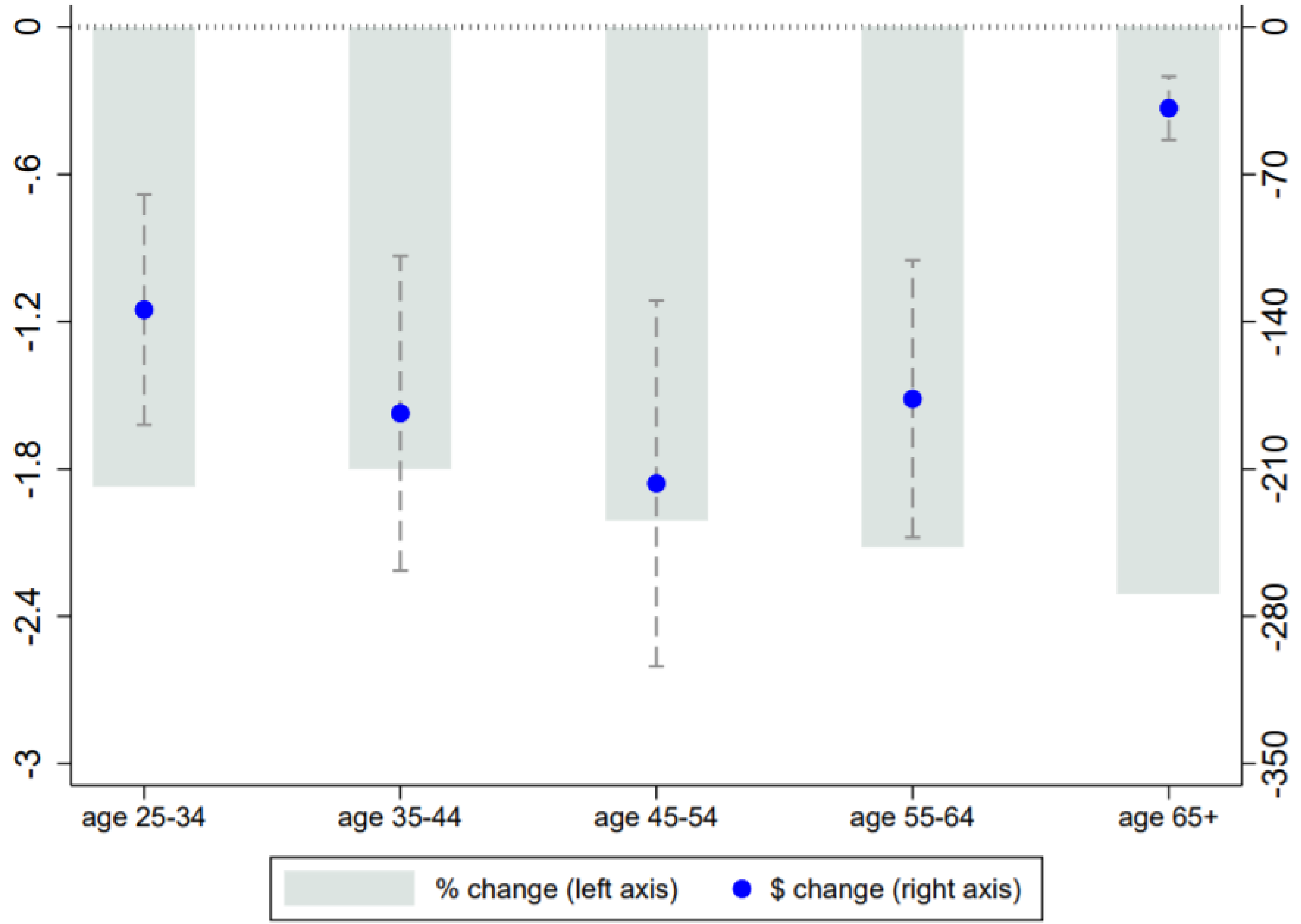
Smoke effects by above vs. below median characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Smoke	-5.976***	-5.366***	-5.749***	-4.095***	-6.524***	-6.794***
	(0.670)	(0.987)	(0.770)	(1.049)	(1.181)	(1.616)
Smoke × $1_{\geq \text{median}}$(urban)	0.860	-	-	-	-	1.244*
	(0.631)	-	-	-	-	(0.688)
Smoke × $1_{\geq \text{median}}$(poverty)	-	0.343	-	-	-	0.478
	-	(0.886)	-	-	-	(0.953)
Smoke × $1_{\geq \text{median}}$(home price)	-	-	0.658	-	-	0.384
	-	-	(0.697)	-	-	(0.763)
Smoke × $1_{\geq \text{median}}$(black)	-	-	-	-2.414**	-	-2.817**
	-	-	-	(0.980)	-	(1.100)
Smoke × $1_{\geq \text{median}}$(avg. $PM_{2.5}$)	-	-	-	-	1.778	1.628
	-	-	-	-	(1.180)	(1.121)
Outcome mean	5,359.7	5,359.7	5,359.7	5,359.7	5,587.1	5,587.1
Observations	160,346	160,346	160,346	160,346	89,020	89,020

Notes: Each column is a separate regression. Indicator variables flag counties with above median: fraction of urban population (Census 2010), fraction of population living under 100% of the Federal Poverty Line (ACS 2007-2016), county median home value (ACS 2007-2016), share of African American population (ACS 2007-2016), and sample-average PM2.5.

Heterogeneity: IV estimates by workers in different age groups

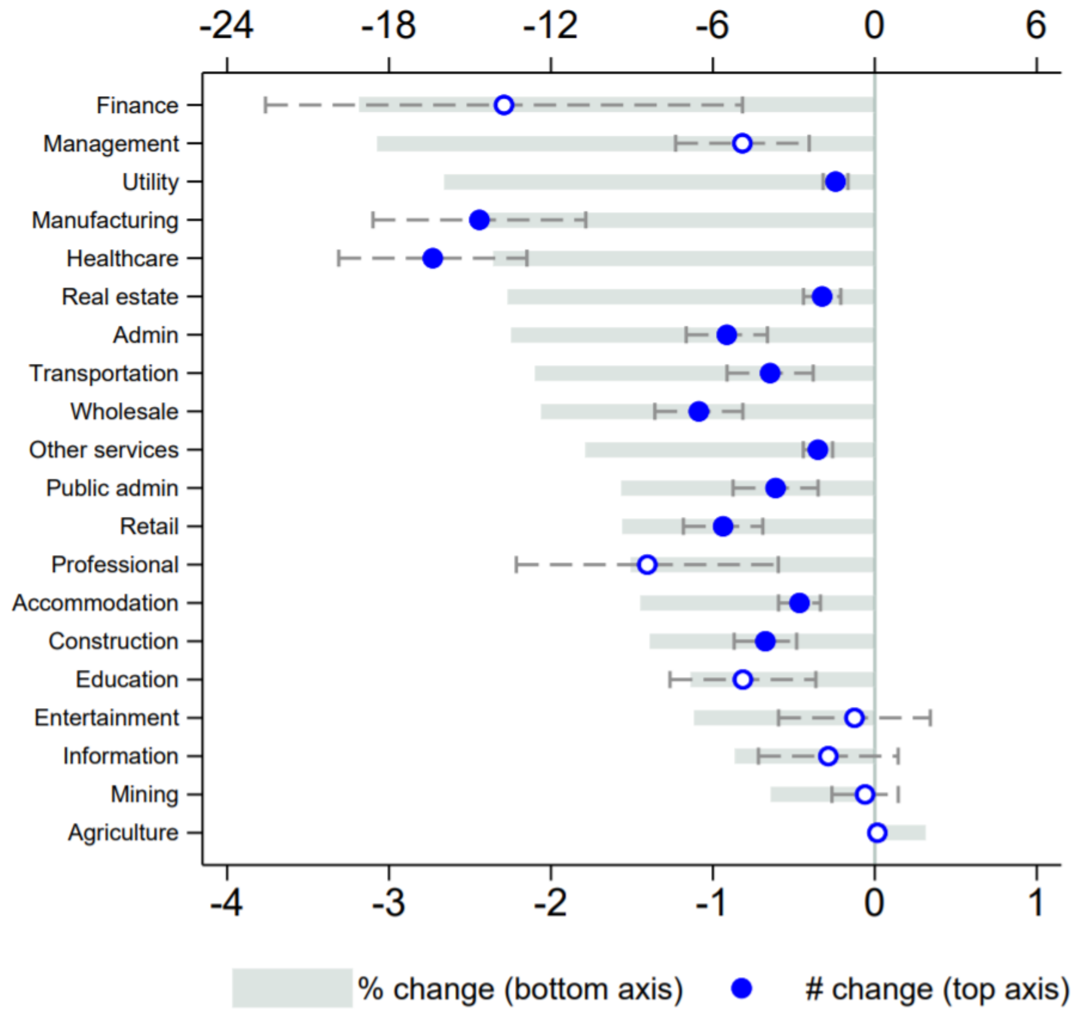
Larger proportional effects for older workers



Notes: Point estimates and range plots show the estimates in levels; bars converts the level estimates to percentage term by dividing the estimates by the average per capita earnings of the corresponding group.

Heterogeneity: IV estimates by workers in different industry sectors

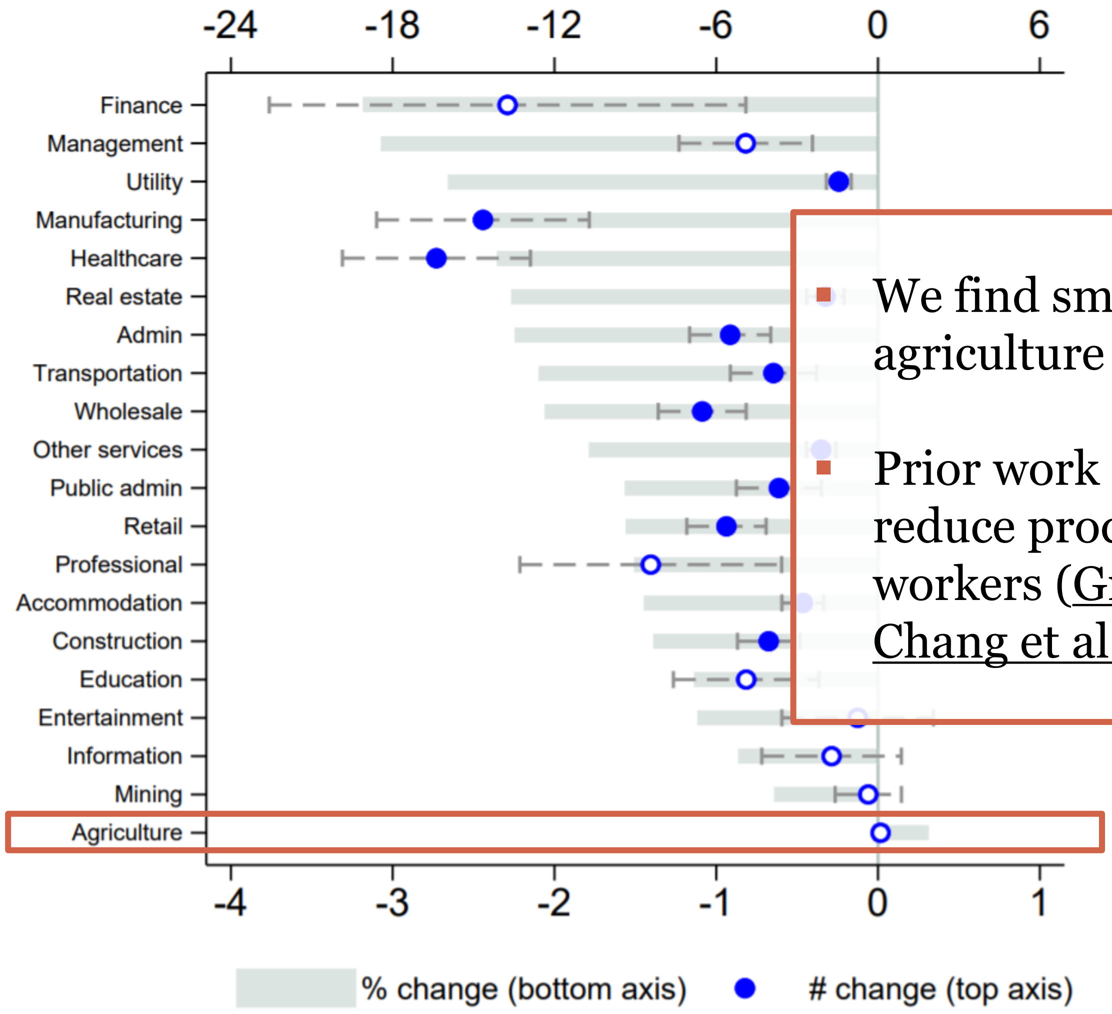
Substantial heterogeneity across industries



Notes: Point estimates and range plots show the estimates in levels; bars converts the level estimates to percentage term by dividing the estimates by the average per capita earnings of the corresponding group. Solid points highlight industries with a family-wise adjusted p-value less than 0.05 based on 100 bootstraps of the free step-down procedure of Westfall and Young (1993).

Heterogeneity: IV estimates by workers in different industry sectors

Substantial heterogeneity across industries



- We find small and imprecise effect on agriculture
- Prior work shows pollution significantly reduce productivity of piece-rate ag workers (Graff Zivin and Neidell, 2012; Chang et al., 2015)

Notes: Point estimates and range plots show the estimates in levels; bars converts the level estimates to percentage term by dividing the estimates by the average per capita earnings of the corresponding group. Solid points highlight industries with a family-wise adjusted p-value less than 0.05 based on 100 bootstraps of the free step-down procedure of Westfall and Young (1993).

Agricultural Effects: **Effects of pollution by 3-digit NACIS industry**

Pollution significantly reduce employments in crop production, but not other sectors

	(1)	(2)	(3)	(4)	(5)	(6)
NAICS code:	11	111	112	113	114	115
	ag total	crop production	animal production	forestry logging	fishing hunting	support activities
$\hat{PM}_{2.5}$	-54.2*	-44.2***	0.7	1.6	-0.7	-26.9
	(29.1)	(15.3)	(1.6)	(1.9)	(1.6)	(23.7)
Outcome mean	5,147.3	2,464.0	735.8	437.5	99.0	2,462.8
Kleibergen-Paap F	186.2	160.0	134.3	138.5	15.1	140.5
Observations	68,846	50,816	43,921	19,841	3,582	38,634

Notes: Each cell is a separate regression. The dependent variable is QWI employment for the corresponding sector indicated by the column title.

Comparison with Health Effects of PM2.5

- Labor market costs
  - Loss of earnings: $123 billion per year per 1 ug/m3 increase in PM2.5
  - Paper shows welfare loss depends on whether lost days at work are replaced with leisure, sick days, and whether they lead to lower wages
  - We estimate social welfare loss to range between $31 billion - $92 billion per year

- Mortality costs
  - Use established estimates by Deryugina et al. (2019): 3,383 additional deaths annually among the U.S. elderly population (aged 65+) per 1 ug/m3 increase in PM2.5
  - Value of statistical life (VSL) estimate ranges between $8 billion - $ 31 billion per year

- This back-of-envelope calculation suggests that labor market responses comprise a large share of the welfare costs of wildfire smoke; such costs should be taken into account when evaluating the overall costs of air pollution