Smoked Out: The Effect of Wildfire Smoke on Labor Market Outcomes

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The 2003 Cedar Fire, caused by a novice hunter who lost his hunting partner and started a signal for rescue. Note other fires.

Research Questions

Does air pollution affect aggregate labor market outcomes?

What can wildfire smoke variation say about mechanisms?

Are labor market effects important in welfare costs of pollution?

Several mechanisms from previous research:

- 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

$\rightarrow$ Most isolate variation in unique settings, with large shocks and/or special populations to identify particular mechanisms

Our Study

Use new satellite-derived dataset with position and the shape of smoke plumes emitted by large wildfires

- Plausibly exogenous seasonal variation with national exposure
  - → National exposure key for policy, external validity
  - → Wildfire produces 16% of $PM_{2.5}$ in the United States
  - → Caveat: chemical composition differs from other sources of air pollution
- Create annual panel of total days of smoke exposure by county
  - → Controls for weather: temperature, wind, rain
  - → Smoke travels 100s and 1000s of miles — drop fire-affected counties in most specification

What We Find

Smoke Reduces Annual Wage Income

- Each smoke day $\downarrow$ per cap income 0.05% in year of exposure
- Effects persist into the following year
- Satellite detects smoke on 4.6% of people-days $\Rightarrow$ 1.21%, or \$95 billion in labor income lost to wildfires each year

Smoke Reduces LFP and Increases SSA Claiming

- Decrease in LFP, increase in SSA beneficiaries and total benefits
- Explains $\approx$ 20% of total earnings loss

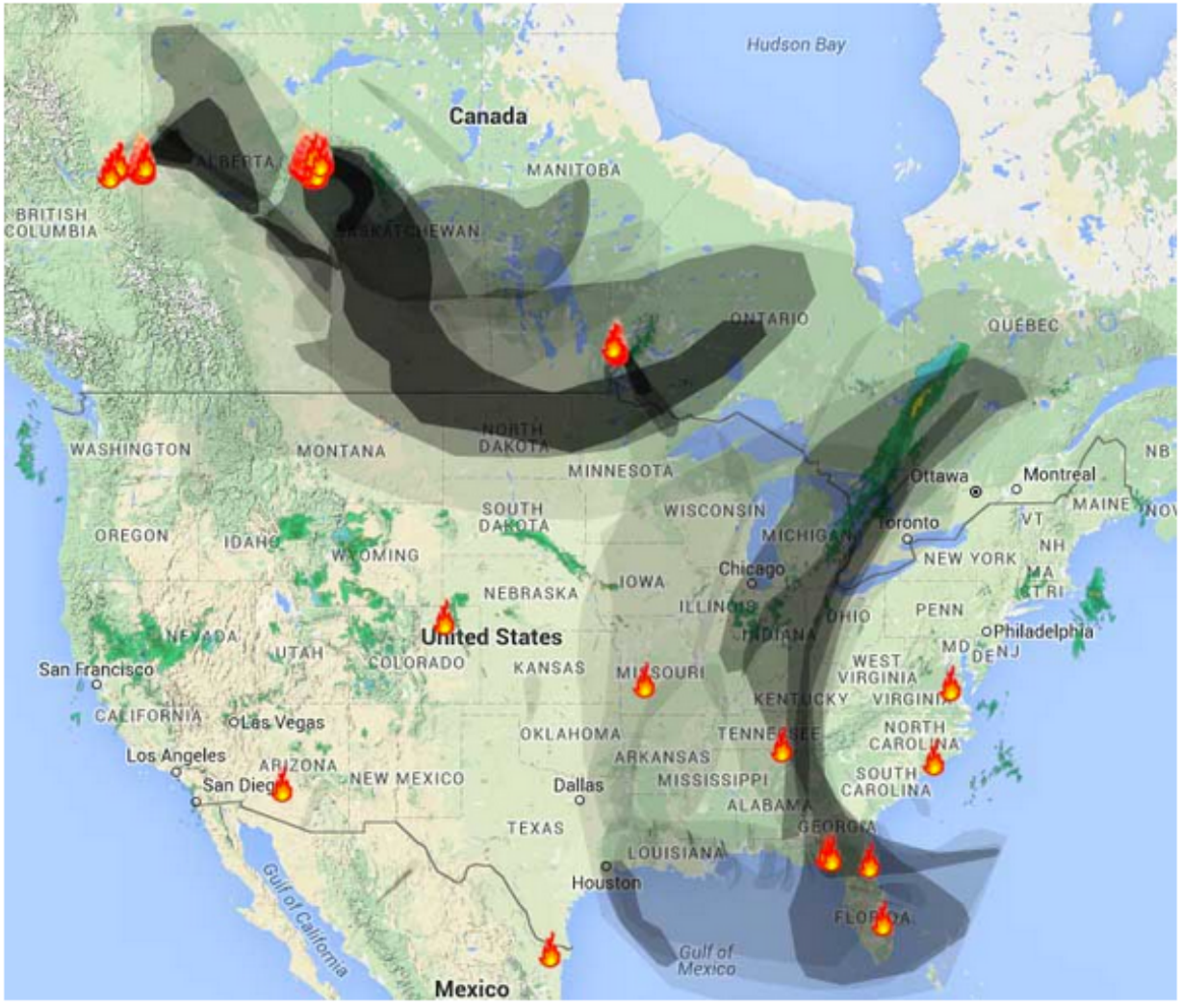
Welfare Costs on Labor Market Exceed VSL-weighted Mortality

- \$9 billion per year in mortality costs using same exposure
  - Mortality usually thought to dominate welfare costs of pollution

Measurement of Smoke Exposure

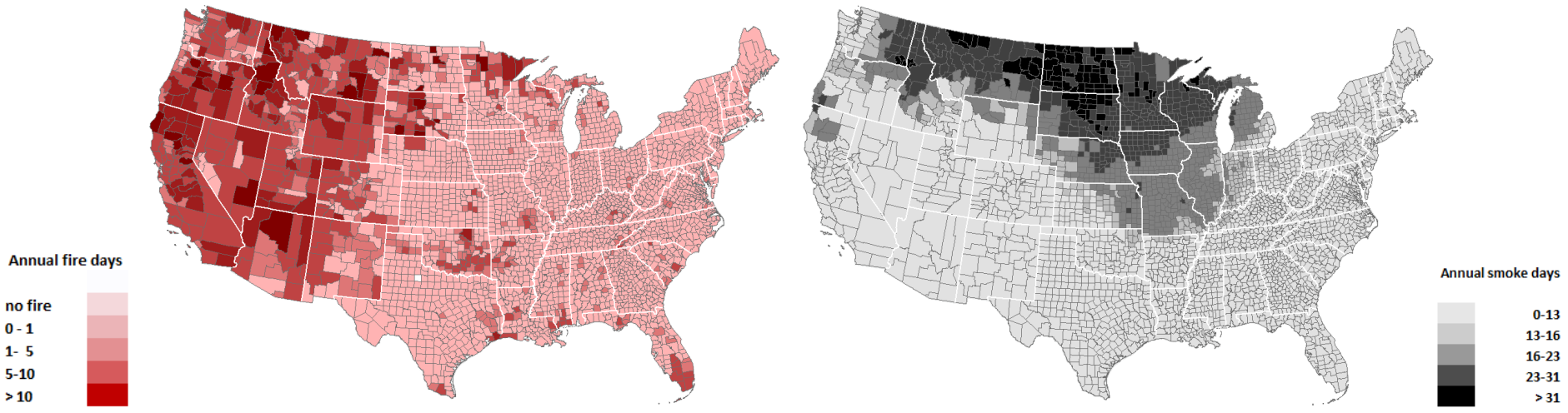
- NOAA Hazard Mapping System (2002 - present)
  - In 1998 wind brought a surge of smoke across the Gulf of Mexico into Texas, Gulf Coast states and beyond
  - In response, NOAA built a team of scientists to produce daily smoke analysis
  - Now integrated as a part of NOAA's forest fire alarming system
  - HMS incorporates information from 2 geostationary (GOES-E/W) and 7 polar orbiting (including Terra and Aqua) satellites
  - Analysts manually draw boundaries of smoke plumes
- We link daily smoke plumes shapefiles to county or ZIP code and calculate number of days the area is exposed to smoke

Fire and Smoke, May 7, 2016



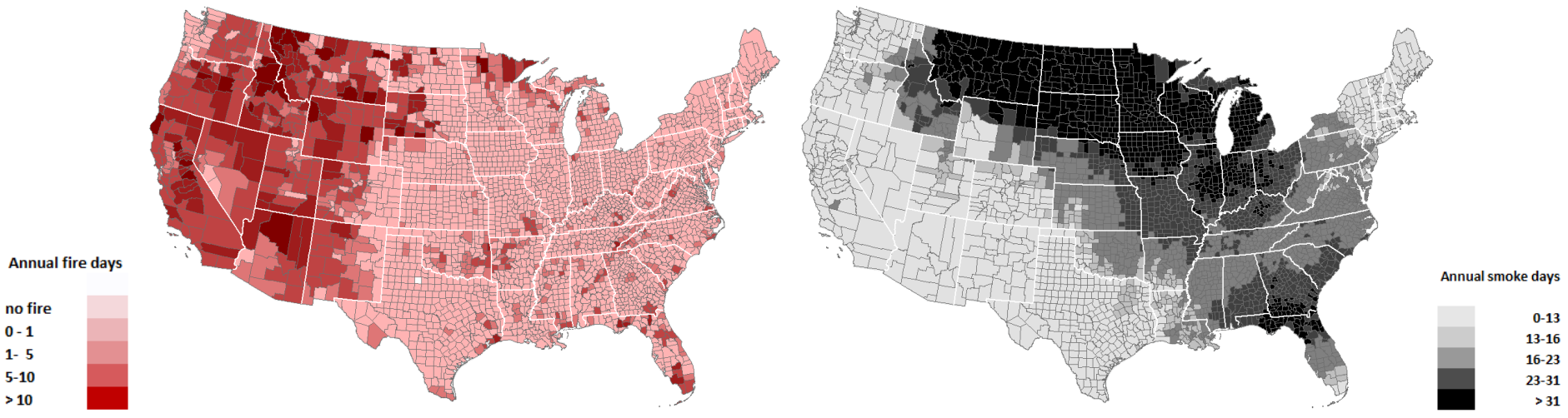
Map of wildfire smoke. WeatherUnderground at 9:20 a.m. May 7, 2016

County-Level Fire Days (left) vs. Smoke Days (right)
Year 2006



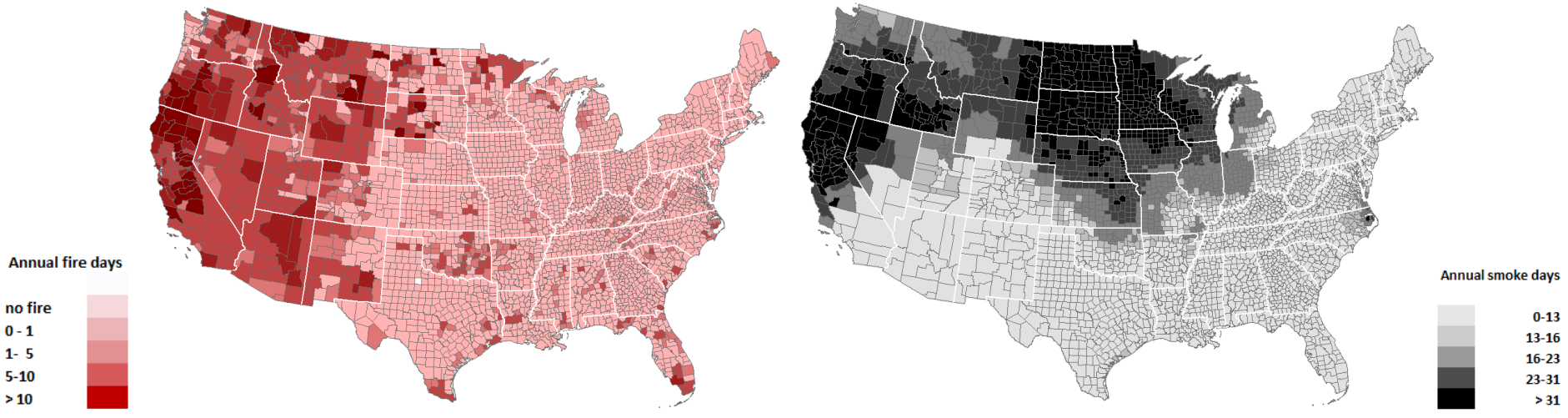
County-level mean annual smoke days 2006-2012 = 16.85 (SD = 15.41).

County-Level Fire Days (left) vs. Smoke Days (right)
Year 2007



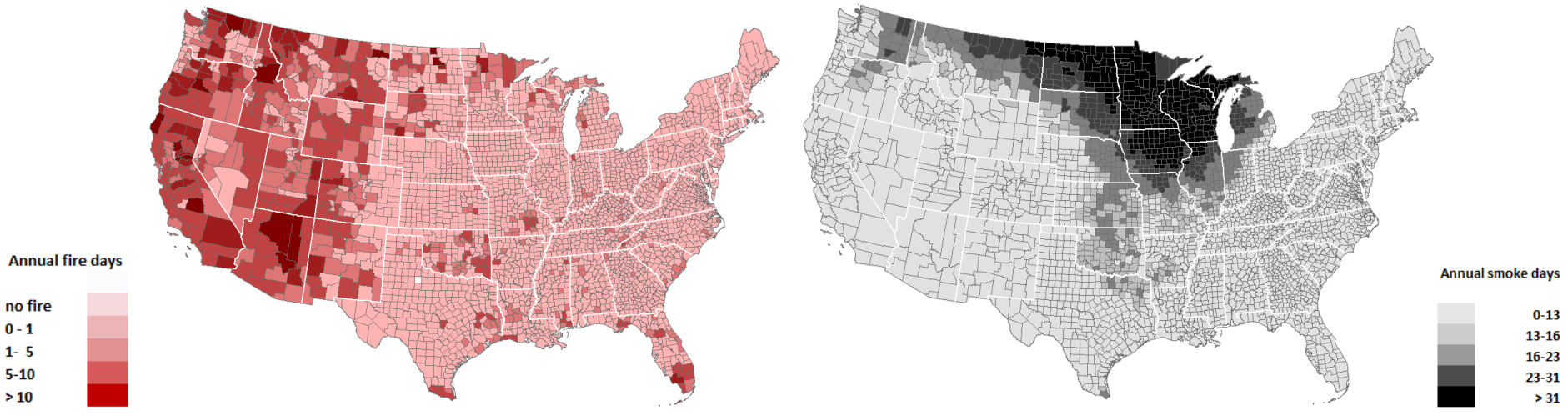
County-level mean annual smoke days 2006-2012 = 16.85 (SD = 15.41).

County-Level Fire Days (left) vs. Smoke Days (right)
Year 2008



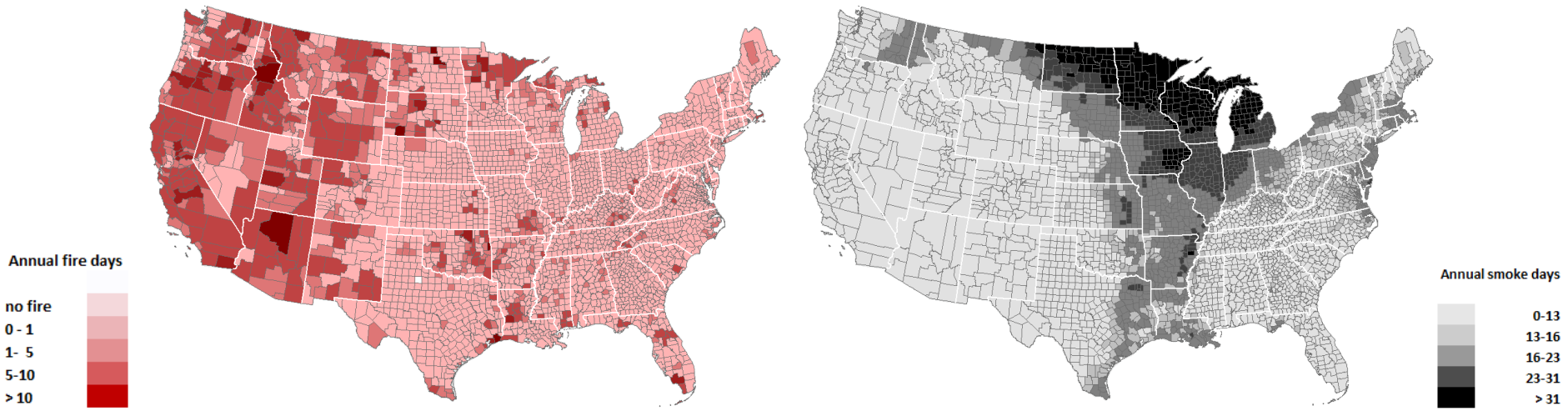
County-level mean annual smoke days 2006-2012 = 16.85 (SD = 15.41).

County-Level Fire Days (left) vs. Smoke Days (right)
Year 2009



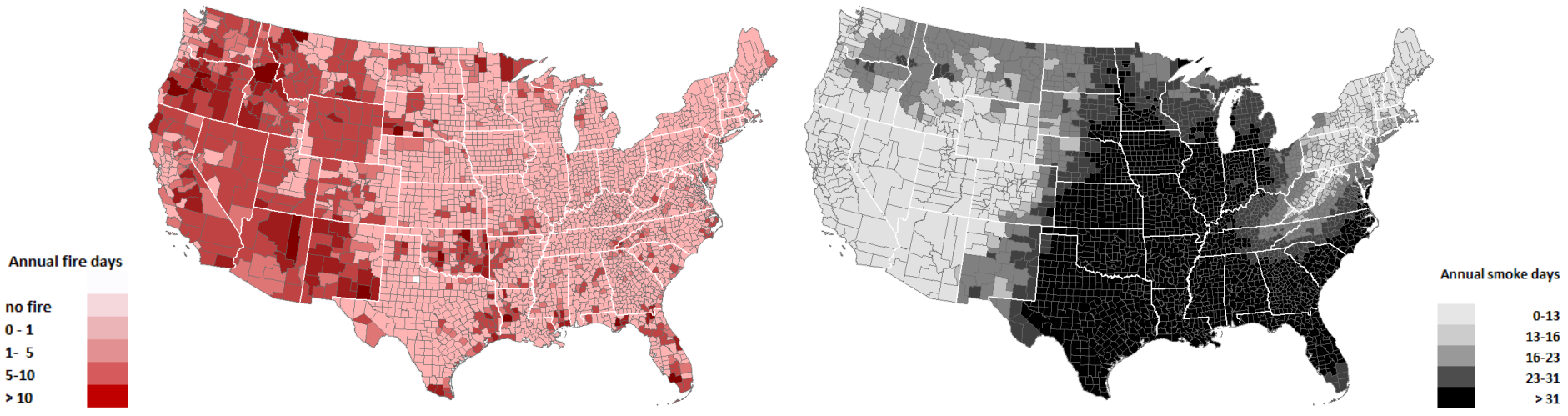
County-level mean annual smoke days 2006-2012 = 16.85 (SD = 15.41).

County-Level Fire Days (left) vs. Smoke Days (right)
Year 2010



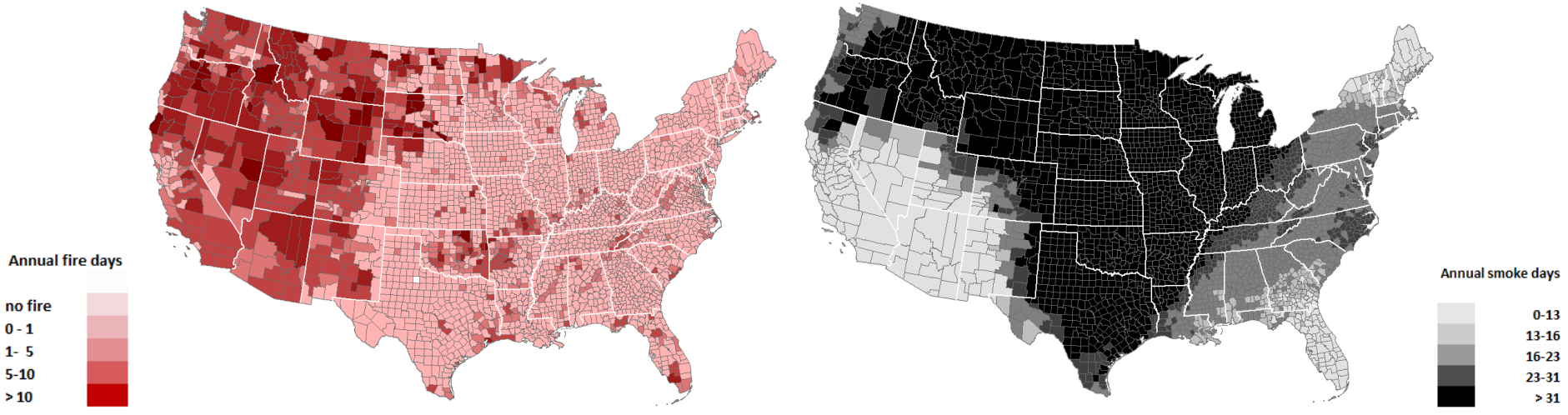
County-level mean annual smoke days 2006-2012 = 16.85 (SD = 15.41).

County-Level Fire Days (left) vs. Smoke Days (right)
Year 2011



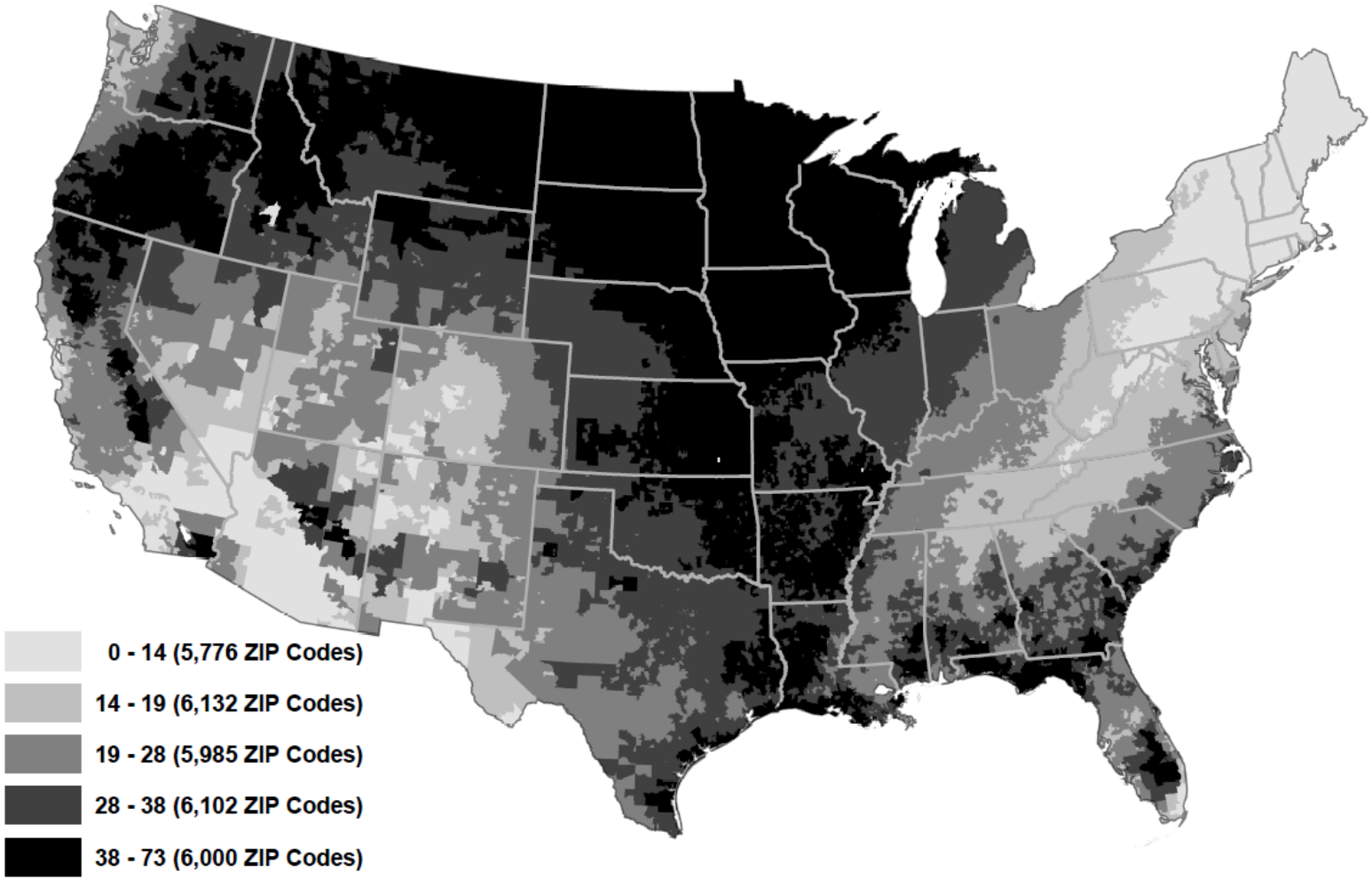
County-level mean annual smoke days 2006-2012 = 16.85 (SD = 15.41).

County-Level Fire Days (left) vs. Smoke Days (right)
Year 2012



County-level mean annual smoke days 2006-2012 = 16.85 (SD = 15.41).

We Have More Granular Smoke Variation at the ZIP-Code Level..
(2006-2012 Average)



Average annual days of smoke exposure at the 5-digit ZIP-code level

Estimation of the Smoke Effect

Lack monitor data in most places, use indicator for smoke day

- $\rightarrow$ Average effect of smoke day
- $\rightarrow$ Drop county codes that report fires in most specs (fire damage, rebuilding and firefighting effects)

Primary specification:

$$Y_{cy} = \beta \cdot Exposure_{cy} + X_{cy}\gamma + \alpha_c + \eta_{s(c)y} + \varepsilon_{cy}$$

- $Exposure_{cy}$ is #days county c is exposed to smoke plumes in year y;
- η_{sy} is a full set of state-by-year dummies;
- α_c are county FEs;
- X_{cy} are weather controls (e.g. temperature, precipitation, wind direction, wind speed bins)

- β identifies the effect of one extra day of smoke exposure on outcome Y_{cy}, e.g. (log) per capita labor market income

Table 1: Δ Annual Air Pollution Due to Wildfire Smoke

	(1)	(2)	(3)	(4)	(5)	(6)
Unit of measure	$PM_{2.5}$ $\mu g/m^3$	PM_{10} $\mu g/m^3$	O_3 ppb	CO ppb	NO_2 ppm	SO_2 ppm
Δ Annual pollution level due to 17 days of smoke						
Exposure	0.259***	1.361***	0.217	0.314	-0.198	0.075
	(0.097)	(0.275)	(0.156)	(1.475)	(0.185)	(0.101)
Mean dep. var.	10.72	20.29	30.43	39.42	9.17	2.49
SD dep. var	2.14	5.49	4.38	13.46	4.66	1.83
N	8,130	5,638	9,361	3,426	3,587	5,240
N (counties)	1,459	1,079	1,642	636	691	966

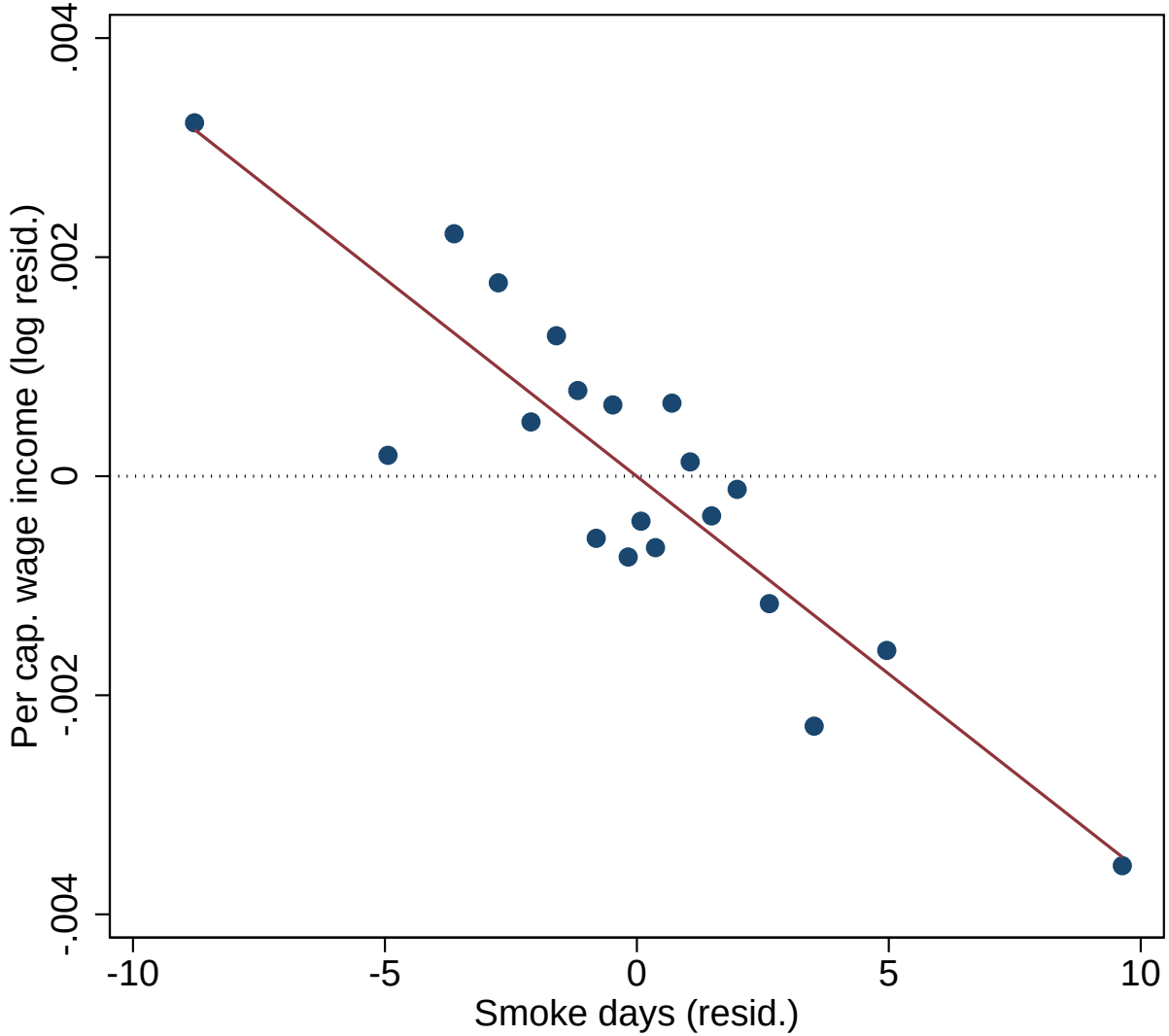
This table presents the average effects of annual county smoke exposure on annual ground-level air pollutant. *Exposure* = Annual smoke days/17, i.e. national avg. annual smoke days. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ Daily Response

Table 2: Δ % Annual Labor Income Per Day of Wildfire Smoke

Dep. var.: Log per capita wage income (coeff. × 100)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Data source:	IRS	CBP	REIS	QCEW	Average		
Smoke days (current)	-0.057**	-0.049*	-0.050**	-0.045**	-0.048**	-0.032*	-0.028
	(0.023)	(0.028)	(0.021)	(0.023)	(0.020)	(0.018)	(0.018)
Smoke days (1st lag)						-0.041**	-0.026
						(0.020)	(0.018)
Smoke days (2nd lag)							-0.036
							(0.027)
N	16,883	16,727	16,710	16,936	16,936	12,193	9,796
N (counties)	2,778	2,775	2,745	2,780	2,780	2,755	2,733

Each column corresponds to a separate regression which uses a different source of earnings measure, indicated by the column names. In columns 5 through 7, the dependent variable is the average across four data sources. *Smoke days* = Annual smoke days. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 1: (Log) Annual Labor Income vs. Annual Smoke Days, Residualized Plot



Average residualized log per capita wage income by 20 equal bins of residualized annual smoke days. The source of wage income measure is ZIP code-level IRS SOI tax statistics data. County-level

Interpreting Earnings Losses

- At 17 days per year, 0.072% loss (current + 1st lag) per smoke day = 1.21% of labor income
- Aggregate losses of $95 billion in 2010 dollars
  - $\Rightarrow$ Workers bear large earnings losses

- What explains magnitude of earnings losses?
  - NOT fire: estimates change little when adding back fire counties; also, effects concentrated in urban areas
  - NOT migration: no change in pop, inflows, or outflows

Mechanisms

- Dynamic pattern of response suggests day-of-exposure avoidance behavior, labor demand, and productivity make small contribution
  - $\Rightarrow$ health and wage effects + interactions with labor market
- In the paper, we show responses on LFP and SSA retirement benefit claims $\Rightarrow$ estimate 20% of total effect
- Also examine evidence for labor demand, industry-specific effects, and economic conditions

Welfare Effects of Lost Labor Earnings

- How to value lost days at work:
  - If replaced with leisure, envelope theorem says near-zero (except significant externality on tax system)
  - If result of constraint (e.g. health, child care), then welfare costs are equal to lost earnings
  - If lower wages, then combines lost wage (welfare $\downarrow$) and endogenous labor supply response (0 effect)

Model : Health and Wage Responses

Model "labor market" welfare effects, W^{LM} through:

1. lost time due to illness
2. lower wages (lower health/human capital and JLS effects) and labor supply response

$$\frac{dW^{LM}}{dc} = h\frac{dw}{dc} - w\frac{ds}{dc}$$

$\Rightarrow$ Lower bound: \$63B, Upper bound = \$95B (total earnings loss)

- Benchmark to VSL mortality costs: $\approx$ \$9 billion

  usually largest component of welfare in direct health costs of air pollution, ex. Deschenes et al 2012

- If firms bear some of cost through sick days or lost productivity, then earnings may underestimate welfare

Table 3: Δ Monthly Mortality Rate Per Day of Wildfire Smoke

Indep. var.: Number of smoke days in a month					
	(1) All age	(2) Age 0-19	(3) Age 20-39	(4) Age 40-59	(5) Age 60+
1-month mortality	0.303**	0.030	0.085	0.019	2.097***
	(0.135)	(0.056)	(0.065)	(0.140)	(0.660)
Mean dep. var.	669.7	48.2	91.8	358.2	2,926.4
3-month mortality	1.117***	-0.019	0.084	0.161	6.468***
	(0.300)	(0.095)	(0.110)	(0.249)	(1.384)
Mean dep. var.	2,006.3	144.8	275.7	1,074.1	8,779.9
6-month mortality	0.861	0.186	-0.101	-0.514	6.286**
	(0.586)	(0.140)	(0.198)	(0.395)	(2.505)
Mean dep. var.	4,011.2	289.6	551.8	2,148.7	17,599.6

Each cell is a separate regression. Mortality rates (deaths per million individuals per month) are measured at all-age (column 1) and by age groups (column 2 to 5). $k-$month mortality is defined as number of deaths in the next k month (including the current month), divided by the number of population alive in the current month. 3- and 6-month mortality regression control additionally for number of smoke days in the look-ahead window. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Conclusions and Future Work

- Wildfire-driven smoke events reduce average annual wage income by 1.21% in 2006-2012
  - Workers bear large costs; firm-side costs remain to be measured
- Extensive margin labor supply and retirement appear to explain significant portion of aggregate effect
- Larger costs than measured in current literature on wildfires (focused mostly on fire damage and health effects), with implications for fire externalities
- Labor market impacts dominate welfare costs compared to mortality

Thank you!

Daily Response

Table 4: Average Effects of Smoke Exposure on EPA's Criteria Pollutants

Panel A. Daily Effect						
Smoke Day	2.190***	3.798***	2.548***	1.009***	0.330***	0.140***
	(0.147)	(0.197)	(0.019)	(0.134)	(0.048)	(0.027)
Mean dep. var.	10.52	21.24	29.79	37.49	9.24	2.26
SD dep. var	6.50	16.32	10.69	20.60	6.95	3.15
N	2,350,113	1,456,654	3,908,791	1,754,629	1,846,530	2,614,670

Annual Response

Migration

Table 5: Annual Migration Effect of Wildfire Smoke

	(1) Number of tax exempt. (log×100)	(2) Per cap out-migrants (log×100)	(3) Per cap in-migrants (log×100)
Exposure	0.345	-0.677	-0.949
	(0.255)	(0.503)	(0.773)
N	16,883	16,912	16,913
N (counties)	2,778	2,780	2,780

Estimates multiplied by average annual exposure. Both out- and in-migrants flows have a mean of roughly 46 migrants per 1,000 individuals per county × year. All regressions exclude counties with wildfires in the year. Standard errors are two-way clustered at the county and the state×year level.

Comparisons to Previous Estimates

Implied earnings effect (annual): +10% $PM_{2.5}$ $\Rightarrow$ -2.5% earnings

- Chang et al 2016 (daily): +10% $PM_{2.5}$ $\Rightarrow$ -0.6% earnings
- Hanna and Oliva 2015 (weekly): -10% SO_2 $\Rightarrow$ +1.5% hrs worked
- Aragon et al 2017 (weekly): +10% $PM_{2.5}$ $\Rightarrow$ -2.2% hrs worked
- Isen et al 2017 (LR): -10% TSP at birth $\Rightarrow$ +1% earnings at age 30

Implied $PM_{2.5}$-adult mortality effect (monthly): +10 ug/m^3 $\Rightarrow$ +1.7% all-age

- Epidemiology corr. (daily): +10 ug/m^3 $\Rightarrow$ 0.5-3% all-age
- Deryugina et al 2017 (daily): +10 ug/m^3 $\Rightarrow$ 0.5-3% age 65+
- Existing LR estimates much ($>$ 40%) larger (ex, Anderson 2016; Chen et al 2013; Ebenstein et al 2017)

Industry Total Earnings Effects

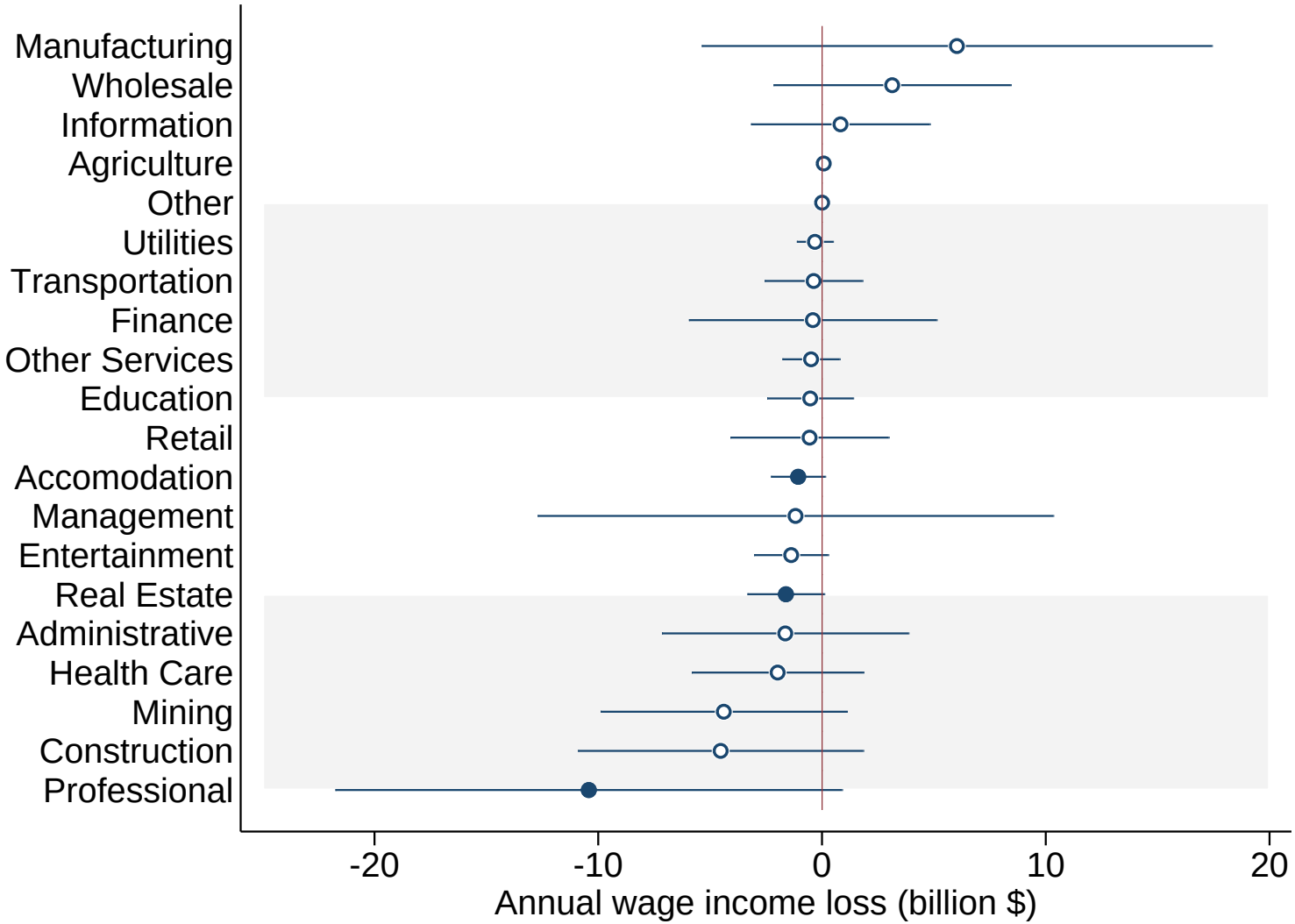
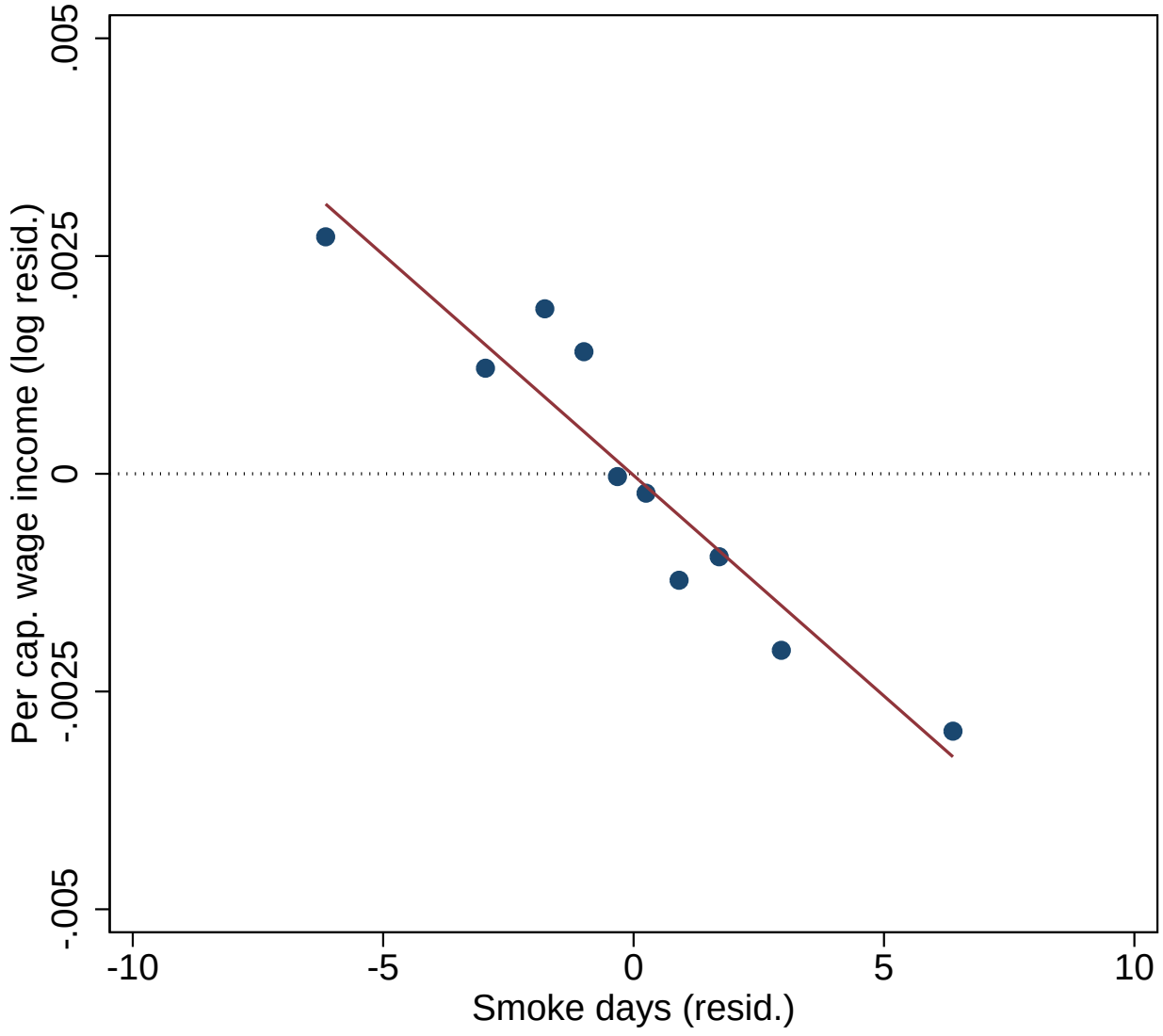


Table 6: Labor Demand: Total Employment and Weekends

	(1) Employment count (log)	(2) Per cap. wage income (log)
Exposure	0.009	
	(0.058)	
Exposure (weekdays)		-0.070
		(0.071)
Exposure (weekends)		-0.267*
		(0.146)
N	161,102	177,482
N (ZIP Codes)	27,301	28,725

Exposure measure the number of days the PUMA or ZIP is exposed to wildfire smoke plumes. Weather controls include ZIP-year temperature and rainfall bins. *** $p<0.01$, ** $p<0.05$, * $p<0.1$



Note: County-level IRS data. ZIP code-level

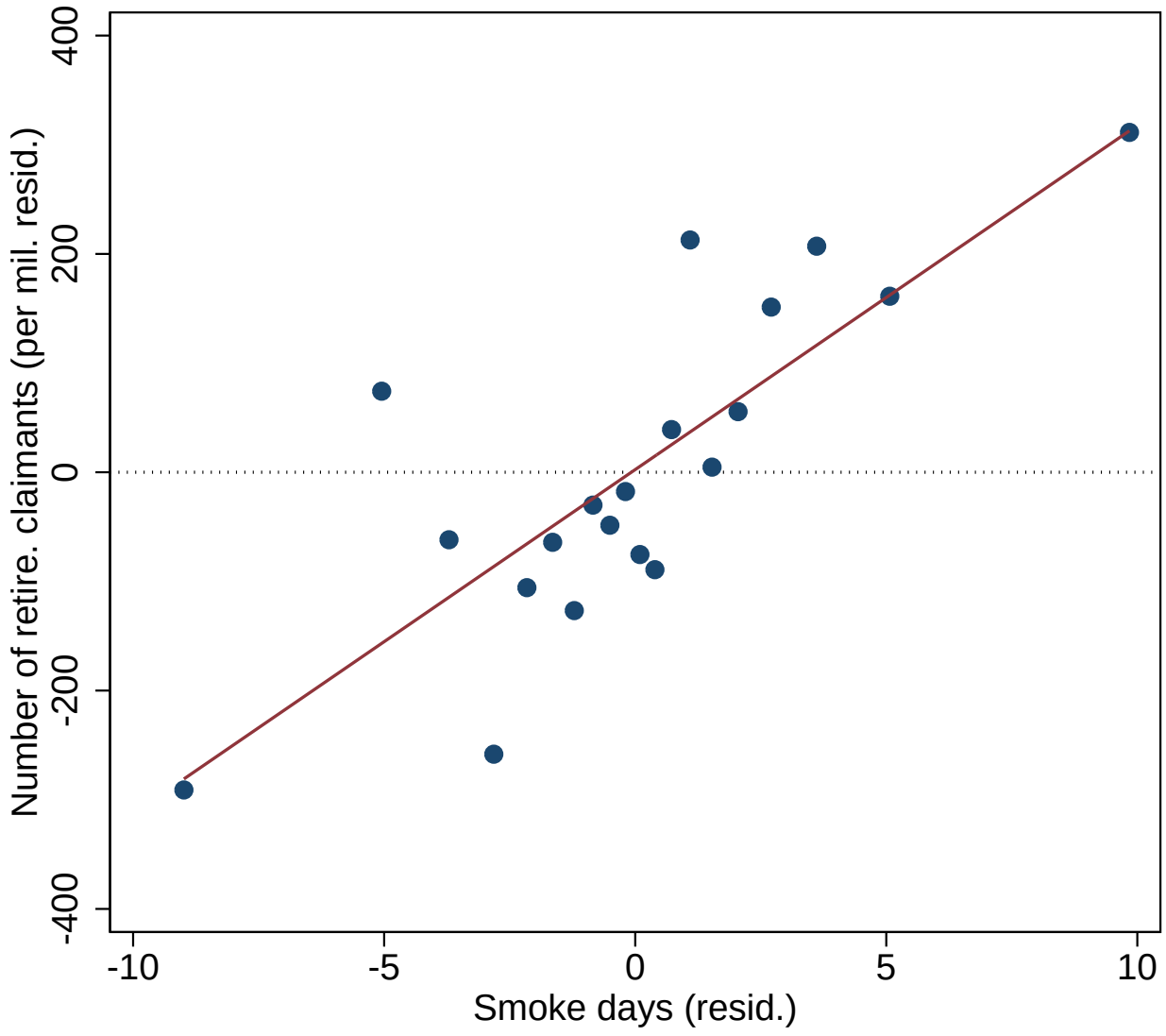
Extensive Margin Labor Supply and Retirement

- Young and old are most vulnerable to air pollution
  - Existing evidence largely focuses on mortality effects when considering elderly
- And, labor market disruptions near retirement can be very costly
  - Difficult to find a new job, often must take significant wage cut
  - May be forced into retirement, DWL if claim social security early
- Novel mechanism in literature on effects of air pollution

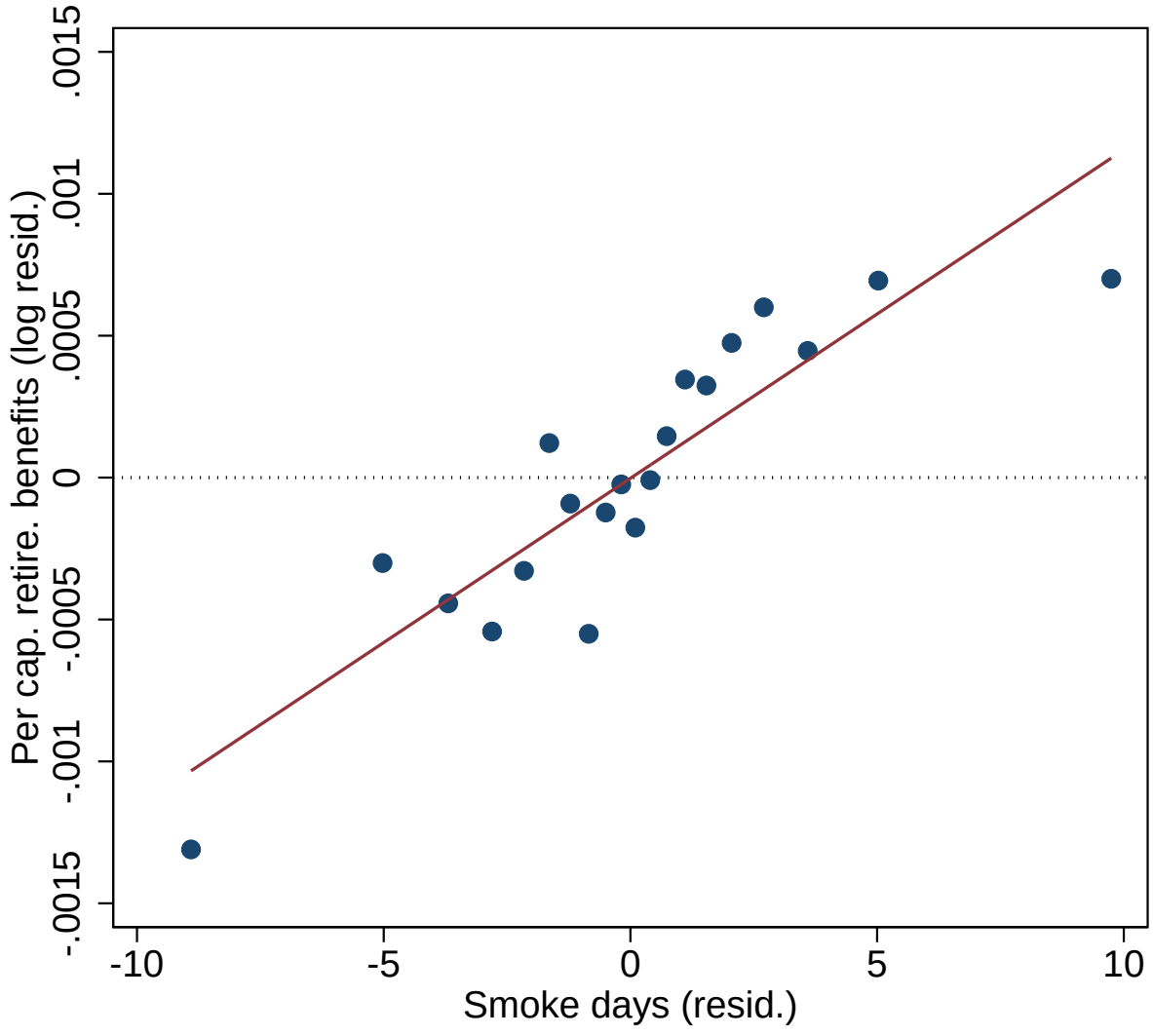
Table 7: Effect of Smoke Exposure on LFP and Retirement Income

Source of measure:	ACS	BLS LAU	Social Security Admin.	
	(1)	(2)	(3)	(4)
	LFP (per million)	LFP (per million)	Number of retire. claimants (per million)	Log per claimant retire. benefits (coeff. $\times$ 365)
Panel A. Independent variable = smoke (days)				
Exposure	-95.9**	-32.31**	32.19**	0.041***
	(43.8)	(16.30)	(14.41)	(0.013)
Panel B. Independent variable = "Deep" smoke (days)				
Exposure		-73.90***	27.61*	0.034**
		(27.04)	(15.22)	(0.014)
Mean dep. var.	0.72	490,595	138,750	-
ZIP Code/county/PUMA level?	PUMA	county	ZIP Code	ZIP Code
Annual/monthly level?	annual	monthly	annual	annual
N	8,123,486	244,202	187,468	188,522
N (ZIP Codes/county/PUMA)	2,054	2,993	28,376	28,554

Exposure measure the number of days the area is exposed to wildfire smoke plumes. Weather controls include area-year temperature and rainfall bins. *** $p<0.01$, ** $p<0.05$, * $p<0.1$



Note: Exposure >60 days collapsed into 5-day bins. Lines fit to entire range of data.



Note: Exposure $>$60 days collapsed into 5-day bins. Lines fit to entire range of data.

Extensive Margin Labor Supply and Retirement

- Smoke appears to affect timing of retirement and SSA claiming
  - LFP effect in ACS is 95 per million, in LAU is 40; SSA finds 32 new claimants
  - Estimates are a bit noisy, use different geographic units; best guess around 50% of LFP drop shows up as retirement in SSA
  - Elasticity of retirement income wrt wage income is around 1.5-2, beneficiaries wrt wage income around 1 (note this is stock vs flow)
- LFP explains 20% of effect on wage and salary income, retirements 10%

Table 8: Heterogeneity by Economic Status: Wage Income

	(1) Unemployment	(2) Poverty	(3) Home value	(4) Frac. black	(5) Avg. PM_{10}	(6) Frac. urban
Panel A. Dependent variable = Log per cap. wage income (coeff. $\times$ 365)						
Exposure $\times$ $\mathbb{I}(\geq$ median)	-0.082**	-0.150***	-0.10**	-0.155***	-0.145***	-0.138***
	(0.041)	(0.045)	(0.043)	(0.042)	(0.056)	(0.043)
Exposure $\times$ $\mathbb{I}(<$ median)	-0.255***	-0.090*	-0.165***	0.015	-0.158***	0.004
	(0.084)	(0.047)	(0.050)	(0.041)	(0.048)	(0.046)
Equality *p* value	0.038	0.058	0.028	0.000	0.712	0.000
N	177,319	176,829	175,929	187,722	88,079	177,117
N (ZIP Codes)	28,697	28,322	28,076	28,415	13,810	28,474

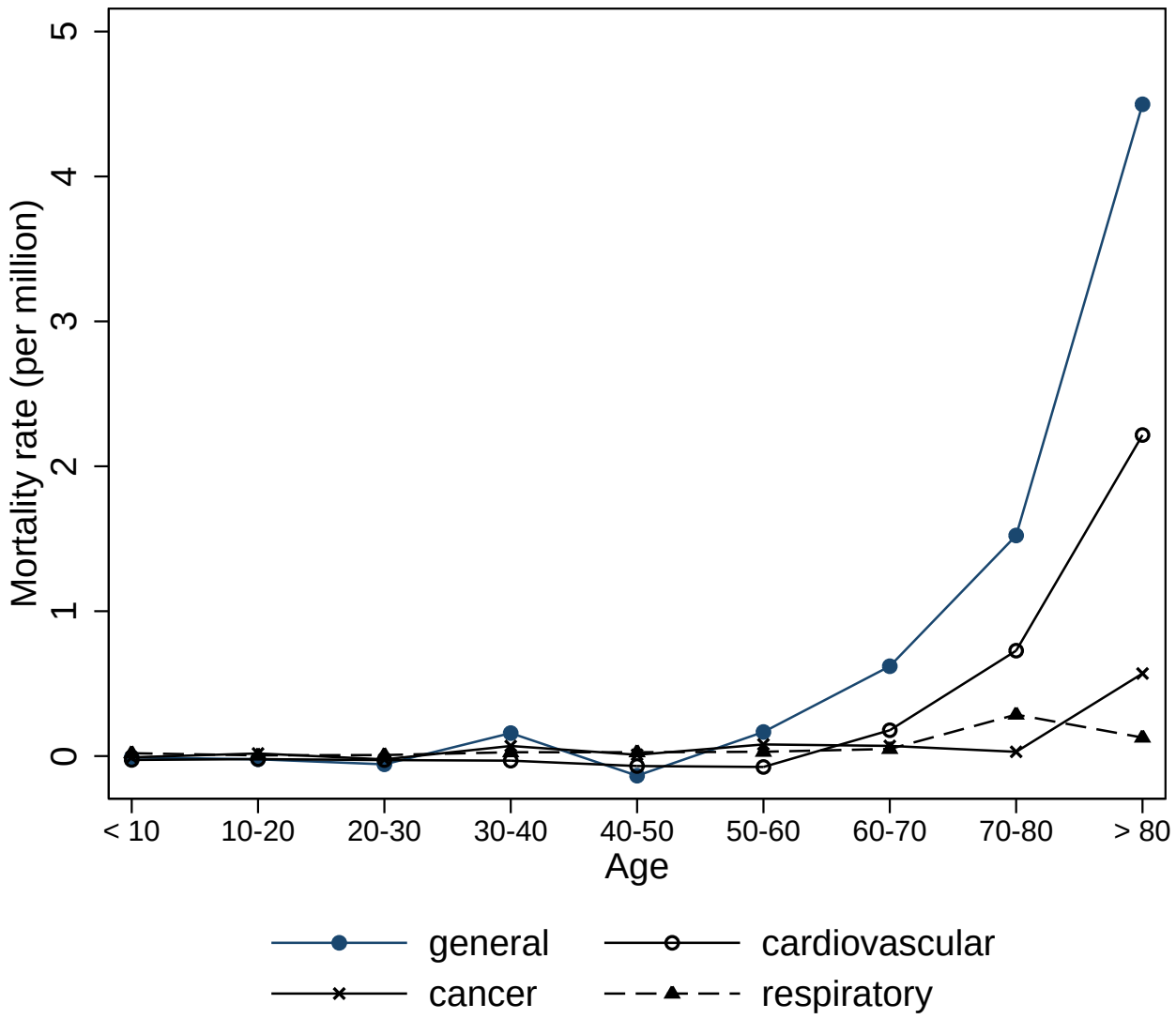
Exposure measure the number of days the PUMA or ZIP is exposed to wildfire smoke plumes. Weather controls include ZIP-year temperature and rainfall bins. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9: Heterogeneity by Economic Status: Retirement

	(1) Unemployment	(2) Poverty	(3) Home value	(4) Frac. black	(5) Avg. PM_{10}	(6) Frac. urban
Panel B. Number of retirement claimants (per million)						
Exposure $\times \mathbb{I}(\geq$ median)	39.28**	-20.01	79.76***	19.58	20.18	27.63*
	(17.37)	(19.32)	(19.26)	(15.62)	(16.20)	(15.28)
Exposure $\times \mathbb{I}(<$ median)	8.03	104.59***	-41.70**	87.26***	55.96***	66.93***
	(20.49)	(19.32)	(19.45)	(18.09)	(18.65)	(17.67)
Equality *p* value	0.164	0.000	0.000	0.000	0.000	0.000
N	177,319	176,829	175,929	187,722	88,079	177,117
N (ZIP Codes)	28,697	28,322	28,076	28,415	13,810	28,474

Exposure measure the number of days the PUMA or ZIP is exposed to wildfire smoke plumes. Weather controls include ZIP-year temperature and rainfall bins. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Mortality Rate by Major Causes



All regressions control for age∗county∗month-of-year fixed effects and age∗state∗year fixed effects. County-year weather controls include 9 daily temperature bins, 6 monthly precipitation bins, 6 daily wind directions bins, and 5 monthly wind speed bins.

Adding it all up: Exposure Heterogeneity

- Three types of exposure heterogeneity: baseline, within-day intensity, length of exposure
  - Baseline (correlated with wealth): no difference in earnings, larger effects for below-median baseline (wealthier) areas in retirement
  - Within-day: larger effects with deep exposure, suggestive of increasing effect size
  - Total annual exposure: modestly declining effect in earnings, linear effect in retirement
  - Also examined spell-length effect, but could not reject linear effect

  Policy implication: Not far from linear $\Rightarrow$ focus on preventing total population exposure to smoke, and secondly, on severity of largest events

Adding it all up: Heterogeneity by Economic Condition

- Different effects for earnings and retirement
  - Earnings losses concentrated in less advantaged, urban areas
  - Retirement increase in more advantaged areas

  $\Rightarrow$ Poorer, urban areas are both more exposed and more responsive to air pollution.
- Possible Explanations:
  - Earnings: hourly workers without sick days, low-earnings self-employed and outdoor workers bear larger costs
  - Retirement: marginal types for retirement are wealthier (consistent with larger effect on SSA benefits than claimants)

Adding it all up: Heterogeneity by Unemployment Rates

- Earnings losses concentrated in low unemployment areas
  - Contrast with earnings losses, concentrated in less advantaged areas
- In separate panel analysis, find same effects with changes in unemployment rate
- Possible Explanations:
  - Earnings: avoidance behavior—during recession, go to work even if you are sick
  - Health effects of economic conditions (Ruhm 2000)
- State of the labor market appears to predict response $\Rightarrow$ Avoidance behavior and smaller welfare costs

Table 10: IV Model

	(1)	(2)	(3)	(4)	(5)
Panel A. Dependent variable: Per cap. wage income (log)					
$PM_{2.5}$ (ug/m^3)	-0.0169***	-0.0149**	-0.0190***	-0.0172***	-0.0149**
	(0.0050)	(0.0073)	(0.0062)	(0.0054)	(0.0075)
O_3 (ppb)		-0.0311			-0.0748
		(0.0847)			(0.0836)
CO (ppm)			0.0012		0.0020
			(0.0017)		(0.0018)
NO_2 (ppb)				-0.0016	0.0025
				(0.0063)	(0.0062)
$F_{\text{1st stage}}$ ($PM_{2.5}$)	5.98	5.98	5.98	5.98	5.98
$F_{\text{1st stage}}$ (O_3)		3.63			3.63
$F_{\text{1st stage}}$ (CO)			1.52		1.52
$F_{\text{1st stage}}$ (NO_2)				3.85	3.85
N	43,860	43,860	43,860	43,860	43,860
N (ZIP Codes)	7,522	7,522	7,522	7,522	7,522

Exposure measure the number of days the PUMA or ZIP is exposed to wildfire smoke plumes. Weather controls include ZIP-year temperature and rainfall bins. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11: IV Model

Panel B. Dependent variable: Number of retire. claimants (per million)					
$PM_{2.5}$ (ug/m^3)	866.2*	1,102.1**	709.4	887.4*	1,185.1*
	(451.9)	(503.3)	(454.8)	(483.9)	(681.2)
O_3 (ppb)		-3,854.5			-8,165.7
		(4,095.7)			(5,648.8)
CO (ppm)			90.6		175.2
			(100.5)		(128.7)
NO_2 (ppb)				92.7	534.8
				(489.9)	(689.0)
$F_{1st\ stage}$ ($PM_{2.5}$)	5.89	5.89	5.89	5.89	5.89
$F_{1st\ stage}$ (O_3)		3.56			3.56
$F_{1st\ stage}$ (CO)			1.47		1.47
$F_{1st\ stage}$ (NO_2)				3.95	3.95
N	44,691	44,691	44,691	44,691	44,691
N (ZIP Codes)	7,471	7,471	7,471	7,471	7,471

Exposure measure the number of days the PUMA or ZIP is exposed to wildfire smoke plumes. Weather controls include ZIP-year temperature and rainfall bins. *** $p<0.01$, ** $p<0.05$, * $p<0.1$