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

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November 2017

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Abstract

This paper examines the labor market effects of air pollution events caused by wildfire smoke. Wind transports smoke hundreds or even thousands of miles from its source, generating plausibly exogenous air pollution events in distant cities. We measure labor market responses to smoke using a novel linkage of satellite images of wildfire smoke plumes in the U.S., pollution monitor data, and labor market outcomes over the period 2006-2012. Each additional day of smoke exposure reduces per capita income by 0.03 percent that year, with income losses continuing into the year following exposure. Consistent with prolonged effects from transient smoke events, we find that smoke exposure reduces labor force participation and increases Social Security claiming. Lost earnings from annual wildfire smoke exposure sum to 1.33 percent of annual labor income, on average. We estimate that the welfare cost of these lost earnings is substantially larger than the mortality cost of wildfire smoke.

JEL Classification: I10, J21, Q51, Q52, Q53, Q54
Keywords: air pollution, labor supply, health, wildfires

*We thank David Card, Olivier Deschênes, Michael Greenstone, Matthew Kotchen, Darren Lubotsky, Max Moritz, Edson Severnini, and seminar participants at University of Chicago-EPIC, University of Illinois at Urbana-Champaign, Hong Kong University of Science and Technology, Midwestern Economics Association Annual Meetings, IZA Conference on Labor Market Effects of Environmental Policies, University of Illinois at Chicago, University of California at Davis, Population Association of America Annual Meetings, and H2D2 at University of Michigan for helpful comments and suggestions, and the W.E. Upjohn Institute for financial support. Molitor acknowledges support by the National Institute on Aging of the National Institutes of Health under award number R01AG053350; the content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. Borgschulte is the corresponding author and can be contacted at markborg@illinois.edu.

Efficient pollution regulation weighs the benefits to society of reduced population exposure against the costs of abatement. Health improvements among children and the elderly traditionally have been thought to constitute most of the welfare gain from improved air quality (OECD, 2016). Previous research argues that health is also a component of human capital, an input in production, but little evidence exists on the direct effect of pollution on aggregate economic activity or labor market outcomes (Graff Zivin and Neidell 2012 and Hanna and Oliva 2015). If reductions in pollution can improve labor market outcomes, then ignoring this benefit will lead to inefficient pollution regulation (Schwartz and Repetto 2000 and Williams III 2003). A key empirical challenge for identifying the causal effect of air pollution on the labor market is finding exogenous variation in pollution that is not itself driven by economic factors, such as regulations, that have a direct effect on economic activity.

This paper provides new evidence on the direct effects of air pollution on U.S. labor market outcomes by leveraging nationwide variation in air quality induced by wildfire smoke. Drifting wildfire smoke provides a plausibly exogenous source of air pollution events that are both geographically dispersed and widespread, so much so that wildfire is an important policy issue in its own right. Wildfires account for one-sixth of the fine particulate matter emitted in the United States, and the National Research Council estimates that each degree Celsius increase in global temperature may lead to a quadrupling of acreage burned.[1] Specifically, we use variation in wildfire smoke exposure to examine the effect of air quality on annual labor income, and provide the first evidence of extensive margin effects of air pollution. To benchmark our estimates, we examine mortality responses, traditionally the largest component of the costs of air pollution on population health.

Our analysis relies on a novel linkage of high-resolution satellite remote sensing data on wildfire smoke plumes in the U.S. with ground pollution monitors and labor market data over

[1] Emissions by source come from the 2011 EPA Emissions Inventory. The National Interagency Fire Center (NIFC) keeps records of wildfires and acreage burned. Climate change is projected to increase temperatures and reduce precipitation, leading to longer and more intense fire seasons. See National Research Council (2011) for more details on this projection, and Moritz et al. (2012) for more on modeling of climate-and-wildfire linkages.

the period 2006-2012. As wind can transport smoke for thousands of miles, smoke events are common throughout the U.S. (Figure **??**, Langmann et al. (2009)). Most smoke events last a few days to a few weeks and have a modest but meaningful impact on air quality. At the county level, an average smoke day adds 2.2 $\mu g/m^3$, or one-third of a standard deviation, in daily airborne particulate matter smaller than 2.5 microns (PM2.5).[2] Our primary analysis uses a panel fixed effects model that leverages variation within counties and across years in the number of days of smoke coverage. The analysis includes controls for weather and aggregate economic conditions (captured by state-year fixed effects) to address other time-varying determinants of earnings that may be correlated with smoke and economic activity.

Several key results emerge from the analysis. First, we document meaningful declines in annual labor income in areas exposed to smoke. Using annual variation in a county's exposure to wildfire smoke, we find a roughly linear and negative relationship between days of smoke exposure and per capita income. To avoid attributing the direct effects of wildfire to the effects of distant smoke, we exclude observations where the county experienced wildfire burning that year.[3] On average, each additional smoke day reduces per capita income in the county by 0.03 percent in the year of exposure, and by an additional 0.05 percent in the year following exposure. We find no discernible effect of smoke after two years. This pattern indicates a prolonged effect of smoke exposure, with the smaller effects in the first year consistent with the concentration of smoke days in the middle and second half of the year. These estimates capture the medium- to long-run impacts of smoke shocks, incorporating possible intertemporal substitution in work effort and lasting effects of illness. As a placebo test, we also find no effect of smoke on income in the previous year. Summing the smoke

[2]Throughout the paper, we refer to wildfire, though some portion of the smoke may arise from intentionally set, or prescribed, burns. Biomass burning may be more harmful to human health than car exhaust and most sources of industrial pollution, because it contains a higher share of volatile organic compounds (VOCs), a particularly harmful class of particulate matter. We discuss this further in Section 1, and estimate the full range of EPA-monitored pollutant responses in Section 3.

[3]The direct effect of wildfires on labor market outcomes is ambiguous. Wildfires may destroy businesses and reduce economic activity while burning, but firefighting and rebuilding may temporarily increase incomes. In robustness checks, our estimates of smoke effects change little when we include counties experiencing wildfire burn.

effects in the year of and year after exposure and multiplying by 16.0, the average number of days counties are exposed to smoke each year, we estimate that wildfire smoke reduces labor income in the U.S. by 1.33 percent each year, or $99.7 billion in 2010.

Second, we find that extensive margin responses can explain an important share of the response in labor income. It is well-known that the young and old are most vulnerable to pollution; however, most studies of the effect of air quality on working age adults and the elderly have focused on health, with a particular focus on mortality.[4] For older workers, frictional labor markets and the availability of retirement benefits may multiply the effect of short-run shocks to health and productivity, as the costs of job loss or transitions between jobs may be larger for them than for younger workers.[5] Consistent with the hypothesis of extensive margin effects on older workers, we find that wildfire smoke decreases labor force participation and increases Social Security claiming. We first document that each day of smoke exposure reduces labor force participation by 0.0098 percentage points, on average. Multiplying this daily effect by the average smoke exposure days per year implies a decrease in labor force participation of 0.16 percentage points from average annual exposure. Under reasonable assumptions about harvesting, the extensive margin effect explains more than 10% of the overall decrease in income. Second, consistent with responses from older workers, we find increases in both the number of Social Security beneficiaries and in the size of benefit payments in exposed areas. This evidence appears to be the first in the literature to link air pollution to retirement responses, and can help explain how short-run changes in air quality associated with wildfire smoke plumes may have lasting impacts on the labor market. It is likely that previous studies have failed to detect such an effect, as very large samples in conjunction with rich geographic variation in pollution events are required in this analysis. In the light of on-going population aging, the link between air pollution and premature

[4]Medical and public health studies find that vulnerability to respiratory and circulatory illness rises with age, suggesting older workers may be particularly responsive to air pollution (e.g., Bentayeb et al. 2012 and Schlenker and Walker 2016). For examples of the mortality literature, see Dockery et al. (1993) and Pope et al. (2009).

[5]See for example, Chan and Stevens (2001) on job search of older workers.

retirement is of increasing policy relevance.

Third, the cost of wildfire smoke to the US labor market is substantially larger than to mortality. Using the same variation in wildfire smoke exposure, we find increased mortality in the months following smoke events. Applying a Value of Stastical Life (VSL) of $100,000 per lost life year, we estimate wildfire smoke-induced mortality imposes costs of $8.6 billion per year. These effects are 16 percent of the lost labor market earnings we document. Under reasonable assumptions about the mechanisms that explain earnings responses, the welfare costs working through the labor market are more than twice as large as the costs arising from mortality, and may be many times larger. These results contrast with previous estimates that find the costs of premature death represent over 80 percent of the total welfare costs of air pollution.[6] However, in the absence of quasi-experimental variation, previous estimates of the aggregate labor market costs of air pollution have relied on gross assumptions in lieu of the direct measurement of losses. To our knowledge, our population-level estimates of mortality are the first of their kind, as is the comparison of mortality and labor market effects using the same quasi-experimental variation.[7]

This paper makes several additional contributions to the literature. First, we provide estimates at a scale far beyond the existing work on air pollution, human capital, and labor market outcomes.[8] This allows us to explore nationally-representative heterogeneity, and

[6]See OECD (2016) for a summary of the literature; to take an example, World Bank; Institute for Health Metrics and Evaluation (2016) estimates that labor market costs comprise less than 5 percent of the total welfare costs of air pollution worldwide and in North America, specifically.

[7]Our approach is similar to the empirical strategy in Deschênes and Greenstone (2011), which documents the effect of extreme heat days on annual income measures, and Deschênes, Greenstone and Shapiro (2012), which uses the comparison of spending on defensive investments to mortality effects to benchmark welfare effects.

[8]This literature has made important progress in document mechanisms that link air pollution to outcomes such as worker productivity, usually in small-scale settings chosen to minimize the confounding effects of changes in economic activity. See Hanna and Oliva (2015) and Aragon, Miranda and Oliva (2016) for air pollution effects on hours worked; Hausman, Ostro and Wise (1984), Hansen and Selte (2000) and Holub, Hospido and Wagner (2016) for sick leave; Graff Zivin and Neidell (2012) and Chang et al. (2014) for the productivity of agricultural workers; Li, Liu and Salvo (2015) and Adhvaryu, Kala and Nyshadham (2016) for the productivity of Chinese and Indian manufacturers, respectively; Chang et al. (2016) for the productivity of indoor call center workers; Lichter, Pestel and Sommer (2015) and Archsmith, Heyes and Saberian (2016) for the performance of soccer players and baseball umpires, respectively; Ebenstein, Lavy and Roth (2016) and Roth (2016) for test score performance. See Graff Zivin and Neidell (2009) and Aldy and Bind (2014) for effects on demand for goods and services, such as for entertainment, hospitality and tourism.

shed light on the relative importance of some mechanisms documented in the previous literature. We find consistent evidence of larger responses in economically disadvantaged areas, measured by the average poverty rate and African-American share of the population; we also find larger responses in urban areas. The larger responses in urban areas further demonstrate that the aggregate effects are not associated with the burning of the fires themselves. We also examine migration responses, changes in the total number of employees in a county, heterogeneous effects by industry, and weekday versus weekend exposures. We find little evidence of changes in population or labor demand. Instead, the pattern of lagged effects and extensive margin responses suggests that health and associated labor supply responses explain most of the effects on labor income.

Second, our results imply an important share of the incidence of increased economic activity resulting from reductions in pollution falls on labor. Conversely, as pollution damages population health, labor bears a large cost of the resulting income losses. Previous results demonstrate impacts on productivity, sick leave, and labor demand; however, the incidence of these costs is difficult to ascertain, as it may differ based on firm and setting. Our results indicate that workers benefit from reduced pollution via both gains in health *and* income.

Finally, we make a direct contribution to the literature on wildfire policy. Wildfire is growing threat in the United States and around the world, driven by population growth and climate change. However, fire is a natural process, and it is not clear how resources should be deployed to fight and manage wildfire. The vast majority of the land burned by wildfire is remote and sparsely populated, where the costs of fighting fires may outweigh the benefits. Allowing fires to burn also cleanses forests and prairies of dead and decaying organic material, thereby preventing the accumulation of fuel that may cause larger and more dangerous fires in the future. Buildup of fuels associated with infrequent large fires and falling investments in clearing and preventative burning has resulted in increased fire management costs, fire-related damage, and uncontrollable megafires (Pyne, 2007).[9] Policy

[9]Megafires are those that burn over 100,000 acres. For a history of wildfire and fire management policy in the United States, see Pyne (2015).

must also contend with the demand for fire services in the wilderness-urban interface (WUI), the growth of residential housing in fire-prone areas.[10] In practice, fire management resources are increasingly focused on preventing or fighting those few large fires which threaten densely populated areas.

Our research suggests that damage from downwind air pollution imposes large externalities working through labor market channels. These social costs should be considered alongside traditional considerations of damage to property, natural resources, and firefighting.[11] Labor market responses lead to decreased tax revenue and result in previously-unappreciated costs on public programs, in addition to the damage to population health. Besides the simple increase in the magnitude of damages, our findings also alter the relative balance between destruction due to burning, and externalities due to downwind smoke. Local and state governments make a number of decisions in wildfire, especially in controlling building in areas vulnerable to wildfires, regulations regarding the removal of brush and other fuels, and firefighting priorities once fires break out. More broadly, visual inspection of satellite images, and the patterns of smoke exposure we document, reveals that a significant percentage of wildfire smoke in the United States originates in Canada or Mexico. A larger share of damages accruing to far away populations implies that these local decisions in land use and firefighting may be sub-optimal. Recent policy reforms have focused on restoring natural fire regimes and on "wildland fire use," allowing already-burning fires to continue to accomplish goals such as fuel reduction (Parsons, Landres and Miller, 2003). Smaller and more frequent fires, such as prescribed burns, may be preferred, particularly as they produce less noxious smoke (Liu et al., 2017).

The paper proceeds as follows. Section 1 provides background on wildfire and a model of the links between air pollution and labor market outcomes. Section 2 describes our data, and Section 3 explains our empirical strategy. Section 4 reports our main results on earnings,

[10] See McCoy and Walsh (2014) for more on wildfire risk and the demand for housing in the WUI, and Wibbenmeyer, Anderson and Plantinga (2016) on the demand for fuel reduction in the WUI.

[11] Kochi et al. (2010) surveys the literature, finding only 6 studies that have quantified the economic cost of wildfire smoke, and none that include economic costs coming through the labor market.

and labor force participation and retirement. Section 5 discusses the welfare costs of wildfire smoke exposure, with particular attention paid to the comparison of labor market impacts to mortality costs. Section 6 concludes.

1 Background and Conceptual Framework

How do transient air pollution events, such as wildfire smoke, affect labor market earnings? A well-developed biomedical, public health and economics literature demonstrates negative effects of air pollution exposure on short-run performance and health outcomes. Wildfire smoke, like other air pollution, contains particulate matter that enters the lungs and can pass into the bloodstream. This fine particulate matter carries with it numerous pollutants, such as ozone, carbon monoxide, atmospheric mercury and a range of volatile organic compounds (VOCs). Exposure to these pollutants diminishes human health and performance. Inert particulate matter may also be harmful to human health. Health effects of exposure can have direct consequences on labor supply, leading to missed days of work and reduced productivity. Concurrent hours responses due to illness have been the traditional focus of research by the EPA and other large research organizations.[12] Although a growing literature documents productivity effects, we know of no estimates of the general incidence on workers.

While wildfire smoke is understood to operate through the same channels as other sources of pollution, the composition of wildfire smoke likely makes it more harmful to human health per unit of measured particular matter than most industrial sources of pollution.[13] Evidence on the effects of wildfire smoke exposure on health largely come from case studies of the

[12]The EPA's usual method measures lost earnings by multiplying the dose-response function, estimated from medical records or taken from previous literature, and associated number of days lost due to a given illness, usually taken from survey evidence. For example, this method would gather data on the increase in asthma attacks on smoky days, and then multiple this by the number of days of work lost due to a typical asthma attack.

[13]Research on the differences in the composition of smoke from biomass burning and car exhaust find higher reactivity of VOCs in smoke, which is consistent with the incomplete burning of the carbon material in a fire relative to internal combustion (e.g. (Verma et al., 2015), Verma et al. 2009, and Bates et al. 2015). Wildfire is noteworthy for containing a more noxious mix of chemicals and high levels of extremely fine particulate matter, than most biomass burns Liu et al. 2017.

extreme wildfire-related smoke events. Two leading examples are Kochi et al. (2012), which evaluates the mortality costs of the 2003 Southern California wildfire seasons, and Kochi et al. (2016), which evaluates hospitalization-related morbidity costs of the 2007 Southern California wildfire seasons. These studies find mortality costs valued (using the EPA's suggested VSL) between $172 million to $1.729 billion, while morbidity costs are much smaller, at $3.4 million.[14] Although they examine different fire seasons, the broad conclusion that mortality costs exceed hospital-related morbidity costs appears robust. Another strand of research documents costs to infant health, which may have large valuations attached to them if damage is long-lasting (Jayachandran (2009) and McCoy and Zhao (2016)).

In addition to direct health effects, it is increasingly recognized that behavioral responses to air pollution pose a deep challenge to translating currently available estimates of the effects of air pollutants to policy-relevant parameters. Graff Zivin and Neidell (2013) surveys the literature on avoidance behavior and discusses the challenges it presents for estimating the effect of air pollution.[15] For wildfire smoke specifically, survey research has documented a number of margins of behavioral response to wildfire smoke, such as spending more time indoors, running air conditioners for longer, and missing work (Richardson, Champ and Loomis (2012) and Jones et al. (2015)). Richardson, Champ and Loomis (2012), examining a single large wildfire in California in 2009, estimates the economic costs of health effects to be primarily comprised of avoidance, defensive actions, and disutility, with only about 10 percent of costs due to illness.

The previous literature suggests that the labor market effects we measure arise from health effects and avoidance during and immediately after air pollution events. However, more significant losses may occur if these direct responses catalyze longer-run labor market effects. Far less is known about the long-run effects of transient air pollution shocks on

[14] These mortality valuations likely overstate the true economic costs due to harvesting effects; the authors note this weakness. Other papers which document effects of wildfire smoke on mortality include Sastry (2002). See Deschênes and Moretti (2009) for a discussion of harvesting and mortality.

[15] For examples of the literature on air pollution and avoidance behavior, see Chay, Greenstone et al. (2005) for long-run responses, including residential sorting, and Moretti and Neidell (2011) for short-run avoidance behavior.

either health or labor markets. Theoretically, short-run health effects of air pollution may result in lasting earnings losses over a longer time period through either health channels or interactions with the labor market. Biomedical mechanisms exist through which short-run exposures may affect medium- and long-run health. Most directly, once particulate matter enters the body, it may take weeks or months for it to be cleared. In addition, transient exposures may result in health events, such as heart attacks or the onset of asthma, reducing health capital and leaving exposed individuals more vulnerable to future health shocks. The health literature has established a role for these type of cumulative insults, but we know of no quasi-experimental evidence for air pollution. The closest study we are aware of is Isen, Rossin-Slater and Walker (2017), which documents long-run effects of exposure to the Clean Air Act around and shortly after birth on adult earnings. On the labor market side, we know that temporary labor market disruptions can have lasting impacts: see, for example, studies of displaced workers and labor market entrants (Jacobson, LaLonde and Sullivan (1993), Kahn (2010), Oreopoulos et al. (2012), Borgschulte and Martorell (2017)). Workers in the United States have varying and often weak job protections when they or a family member falls ill.[16] For more serious illnesses, wages may respond due to lasting changes in workers' productivity or employment. We know of no evidence on the effects of these type of responses to air pollution; however, their importance has been demonstrated in other contexts. For example, lower wages resulting from a health shock is the primary source of earnings losses following hospitalization (Dobkin et al., 2016).

To illustrate the multiple channels of action implied by the combination of direct health effects, behavioral responses, and long-run wage effects, we build a simple model of health and labor supply to connect exposure to airborne pollutants with labor market earnings, our primary outcome measure. We model the utility of a representative agent in response to a fixed dose-response function, $s(c)$, relating exposure to pollution concentration, c, to sick

[16]The Family Medical Leave Act covered 59% of workers in 2012, and allowed them to take up to 12 weeks of unpaid leave for their own serious health condition, or that of a spouse, parent, or child (Klerman, Daley and Pozniak, 2012).

days, $s(c)$. Pollution concentration may represent a vector of harmful components in wildfire smoke. The agent maximizes utility that depends on consumption, X, leisure, l, sick days, s, and exposure, c:

$$\begin{aligned}
&\mathbf{max}_{X,l} U(X, l, s, c) \\
&\text{s.t. } Y + wh \geq X \\
&l = T - s - h
\end{aligned}$$

Consumption will equal non-labor income, Y, and earnings, wh. Wages respond to pollution, $w = w(c)$, due to a combination of responses from three channels: changes in the returns to work arising from a decay in human capital after an illness, from the incidence on workers of labor demand changes, and from direct productivity effects during periods of high pollution. T reflects the total time endowment, from which days of illness, $s(c)$, are directly subtracted. Hours of work, $h = h(w(c), c)$, respond to wages and direct avoidance of high pollution.

The resulting earnings function is:

$$E(c) = w(c) \cdot h(w(c), s(c), c) \tag{1}$$

Taking derivatives and re-arranging yields a decomposition of the reduced form effect:

$$\frac{dE(c)}{dc} = w\Big[\frac{\partial h}{\partial s}\frac{ds}{dc} + \frac{\partial h}{\partial c}\Big] + h\Big[\frac{dw}{dc}\Big](1 + \eta_s) \tag{2}$$

The first bracketed term in Equation 2 captures the direct effects of illness on labor supply. The first term inside the brackets, $\frac{\partial h}{\partial s}\frac{ds}{dc}$, denotes the loss of hours of work to illness, and the second term, $\frac{\partial h}{\partial c}$, reflects avoidance behavior. The second bracketed term, $\frac{dw}{dc}$, captures the effect of pollution on wages. The final term, $(1+\eta_s)$, is the endogenous labor supply response to changes in the wage; as the wage falls with pollution exposure, workers may reduce their hours of work. Thus, we expect the effect of air pollution on earnings to be the sum of the

effects working through the direct effect on hours, and the combined effects of wages and endogenous labor supply response.

The primary focus of the paper is to estimate $\frac{dE(c)}{dc}$, the total response of earnings to variation in air quality. We also examine evidence for the components of the losses, especially the response of hours through a labor force participation channel. Following our main estimates, in Section 5, we return to Equation 2 to guide our analysis of the welfare effects of the lost earnings.

2 Data

The analysis is conducted with a comprehensive database that we compiled on wildfire smoke exposure, air pollution, weather conditions, labor market outcomes, and mortality. These data are sourced from a rich set of remote sensing, environmental monitoring, federal income statistics, national representative surveys, and population census data files. This section describes the construction of the database and the definition of our key variables used in the analysis.

2.1 Wildfire Smoke Data

A key innovation of this analysis is the ability to observe daily wildfire smoke exposure at a fine geographic level over a broad geographic scope. We create this dataset jointly with Miller, Molitor and Zou (2017), using wildfire smoke analysis produced by the National Oceanic and Atmospheric Administration's (NOAA) Hazard Mapping System (HMS). The HMS is a program that utilizes a variety of satellite and spacecraft observations to identify fire and smoke emissions over the contiguous US (Ruminski et al., 2006). An important output of the HMS is the daily geo-referenced smoke plume files, drawn manually by smoke analysts, that represent the outlines of smoke plumes emitted by wildfires. We obtain digital archives of the daily plume files from 2006-2012 and construct our key smoke exposure

variable separately at the county and 5-digit ZIP Code level. To construct our measure of wildfire smoke exposure, we first code whether a county intersects any smoke plume detected by the HMS on that day.[17] We then code a county as exposed to smoke if it is on the interior of the plume, measured by whether it both intersect a smoke plume and is surrounded by other areas exposed to smoke. The results are qualitatively similar, but slightly weaker in some specifications, when we to measure exposure using any intersection with a smoke plume.

We complement satellite smoke observations with wildfire records from the National Fire and Aviation Management group of the Forest Service, which combines records from seven major fire and wildland management agencies.[18] Using this data, we identify more than 140,000 wildfire events from 2006-2012. The primary use of this data is to distinguish areas directly affected by the burning of fires.

2.2 Pollution Data

We link satellite smoke observations with ambient air pollution monitoring data obtained from the US Environmental Protection Agency's (EPA) Air Quality System (AQS). We extract monitor-daily readings for EPA's six "criteria pollutants" including fine particulate matters ($PM_{2.5}$), coarse particulate matters (PM_{10}), ozone (O_3), carbon monoxide (CO), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2). We focus on these pollutants because their concentrations are expected to elevate during wildfire events and they are recognized by the EPA to be among the most important pollutants to human health.

To measure air pollution at the local level, for each pollutant we take the weighted average of all readings from monitors that fall within 20 miles from the area's centroid, where the weights used are inverse monitor-to-centroid distance. Depending on the sparsity

[17] In producing smoke plume outlines, the HMS uses data from the Geostationary Operational Environmental Satellite (GOES) visible band imagery available at the 1 km resolution. The granular resolution enables us to explore geographically fine variations in exposure at the county and ZIP Code level.

[18] These include Bureau of Indian Affairs, Bureau of Land Management, Bureau of Reclamation, California Department of Forestry and Fire Protection, National Park Service Fire and Aviation Management, US Fish & Wildlife Service, and Forest Service.

of the monitoring network, a significant number of areas have no pollution monitors within a 20-mile radius and therefore are missing pollution data. Pollution readings can differ by pollutant, as well: 1642 counties have O_3 data, while we are able to obtain NO_2 observations for 691 (Table 2).

2.3 Weather Data

The analysis includes a flexible set of control variables for temperature, precipitation and wind patterns. Temperature and precipitation data are from the National Climatic Data Center's Global Historical Climatology Network (GHCN) which provides station-daily level information on minimum temperature, maximum temperature, and total precipitation. To construct weather conditions at the local level, we average daily weather readings from stations that fall within 20 miles from the county or ZIP code's centroid, weighting readings by inverse station-to-centroid distance.

We obtain wind speed and wind direction data from the National Centers for Environmental Information's North American Regional Reanalysis (NARR). NARR divides the US into 32km×32km grids, and for each grid-day it provides data on the East-West wind vector ("u-wind") and the North-South wind vector ("v-wind") which together characterize wind-speed and direction. Given the resolution of the data, we construct wind conditions at the county level by first linearly interpolating u-wind and v-wind vectors at the grid centroids to the county centroid, and then converting u-wind and v-wind at the county centroid into wind speed and wind direction.

2.4 Earnings Data

Our main earnings analysis uses outcome data from four sources. The first source for earnings is the Internal Revenue Service's (IRS) Individual Income Tax Statistics (SOI). This data is based on stratified probability samples of individual income tax returns Forms 1040,

1040A, and 1040EZ filed with the IRS.[19] For each year, we observe county and ZIP Code level aggregate wages and salaries. We also observe the number of personal exemptions within each area, which we use to convert earnings to the per capita level. The second dataset we use is the Census Bureau's County Business Patterns (CBP), which is based on the Census Bureau's Business Register that contains payroll and employment information derived from administrative records for the universe of firms.[20] The third and fourth county-level earnings measures we use come from the Regional Economic Information System (REIS) from the Bureau of Economic Analysis, and the Quarterly Census of Employment and Wages (QCEW).

While all four earnings sources approach full coverage of labor earnings in the United State, each source has distinct construction. For example, the IRS data will only include workers who file tax returns by the end of the calendar year which follows the year of tax liability; of course, under- and mis-reporting may occur in this data. The other three sources largely rely on firm-provided administrative data, and have slightly different coverage. CBP excludes data on self-employed individuals, employees of private households, railroad employees, agricultural production employees, and most government employees, whereas REIS includes these workers. QCEW, on the other hand, excludes members of the armed forces, self-employed individuals, proprietors, and railroad employees. By using four different data source, we can replicate the main finding and demonstrate robustness to the construction of aggregate labor income.

2.5 Labor Force Status and Social Security Data

We draw county-level labor force participation information from two sources. First, we use Local Area Unemployment Statistics (LAUS) published by the Bureau of Labor Statistics. LAUS contains county-level labor force estimates produced through a building-block ap-

[19] <https://www.irs.gov/pub/irs-soi/sampling.pdf>

[20] CBP's payroll measure is based exclusively on administrative records for single-unit companies. For multi-unit companies, CBP's payroll information comes from a combination of administrative records with Census data. See<http://www.census.gov/econ/cbp/methodology.htm>.

proach that combines data from national representative surveys and state unemployment insurance systems.[21] Second, we use micro level data from all individuals aged over 25 that appear in the 2007-2011 American Community Survey.[22] These five repeated cross sections include more than 8 million individual-year observations with detailed demographic and labor force participation information.

We measure number of retirement claimants and benefits at the ZIP Code level using the Social Security Administration's (SSA) annual publications of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries statistics. The SSA produce these statistics using its Master Beneficiary Record which covers the universe of Social Security beneficiaries who are ever entitled to receive retirement and survivors insurance or disability insurance benefits. For each ZIP Code-year we observe number of retired beneficiaries as well as information on retirement benefits paid out to claimants in that ZIP Code.

2.6 Mortality Data

Mortality outcomes are measured in micro-data provided by the National Vital Statistics System. The underlying data is taken from death certificates which contain age of death. We use the restricted data files containing month of death and all counties in the United States to link mortality outcomes to smoke exposure. The data is available for the entire sample period, 2006-2012, and contains 17.29 million deaths.

[21] LAUS county level estimates use survey data from the Current Population Survey, the Current Employment Statistics survey, and the American Community Survey (ACS). See <http://www.bls.gov/lau/lauov.htm>.

[22] Since we measure individuals' smoke exposure by their residence county's smoke exposure in the previous year, and the smoke data are only available since 2006, the sample can only go back to 2007. Because the analysis identifies the impact of smoke using within residence county variations in exposure, we also cannot use the 2012 ACS due to a change in delineation of residence county.

3 Empirical Framework

Researchers who study the labor market effects of environmental hazards face three primary challenges to identify the causal effects of air pollution on labor markets. First, observational correlations between air pollution and economic activity may be due in part to the causal effect of the economic activity on air pollution, or the confounding effects of the air pollution source, such as the effect of fires burning. As a result, finding a valid instrument for air pollution that does not have a direct effect on labor markets is difficult. For example, policy instruments which reduce air pollution may impose direct effects on the regulated markets. Second, transient changes in air pollution may induce short-run effects that reflect intertemporal substitution, rather than true welfare-reducing labor market effects. Third, existing evidence of pollution and labor markets has generally focused on case studies of specific industries or regions. These estimates may not extrapolate to national effects, and may not generate sufficient variation to study extreme outcomes, such as retirement or mortality. Moreover, these settings may not permit direct comparison of estimates to established effects in the literature.

3.1 Wildfire Smoke Exposure

We use annual variation in regional wildfire smoke exposure to identify the causal effects of transient air pollution shocks on labor markets. A few key features of wildfire smoke permits a research design that addresses the identification challenges described above.

First, wildfire smoke plumes are a natural source of air pollution, traveling hundreds or even thousands of miles downwind, affecting cities at great distances from the fire itself. Table 1 provides summary statistics for the frequency of the events and the average distance to the nearest fire. The average county intersects a smoke plume on 30.6 days per year, with 16.0 days coded as exposure, i.e. on the interior of the plume. Figure 1 presents the spatial patterns of smoke exposure. As can be seen, smoke exposure is concentrated in the upper

Midwest, but exhibits significant year-to-year variation. Importantly for our study focused on air pollution, the pattern of smoke exposure differs markedly from wildfire footprints. Thus, we can study effects of downwind smoke exposure separated from direct damages caused by occurrences of wildfires. The majority of our analysis excludes counties where fires burn.

Second, smoke shocks give rise to spikes in air pollution concentration with the average magnitude large enough for us to expect significant health and behavioral responses. The upper panel of Table 2 shows that wildfire smoke increases concentrations of the 6 EPA criteria pollutants we examine, with the largest responses in particulate matter and ozone. An average smoky day increases $PM_{2.5}$ by 2.2 $\mu g/m^3$ on the day of exposure, more than a third of a standard deviation in the distribution of daily particulate matter. When we examine the cumulative effect of smoke days on annual pollution measures in the lower panel of Table 2, we see that smoke increases the average level of $PM_{2.5}$ by 0.219 $\mu g/m^3$. This implies that each day of exposure contributes 4.8 $\mu g/m^3$ when exposure is aggregated to the annual level, implying that particulate matter lingers in the air, increasing pollution levels on days that are not coded as smoke exposure days in the satellite data.

Third, most wildfire smoke events induce modest, largely imperceptible, changes in air quality, meaning that our estimates are not driven by a small number of intense smoke exposure days. A potential concern with using wildfire smoke is that extreme wildfire smoke events generate substantial news coverage, possibly triggering behavioral responses that would not be present with normal sources of air pollution. However, the vast majority of smoke exposure days in our data lie within the normally experienced levels of air quality. To examine this, we construct the distribution of the smoke-day increase in $PM_{2.5}$ above the average level at a monitor.[23] A smoke day in the 5th percentile of this distribution increases $PM_{2.5}$ by 1 $\mu g/m^3$, while a smoke day in the 95th percentile increases $PM_{2.5}$ by 5 $\mu g/m^3$. To put this into context, the EPA long-run standard for $PM_{2.5}$ is 15 $\mu g/m^3$, while the daily $PM_{2.5}$

[23] Appendix Figure A.3 reports the results, which are normalized relative to 20 days before exposure.

standard is 35 μg/m^3, far above most exposure levels. Thus, although wildfire smoke is a unique source of pollution, it should not trigger dramatically different behavioral responses, as compared to other changes in air quality. This distributional analysis also substantiates the use of the satellite data to measure smoke exposure, as it allays concerns that the satellite is detecting smoke high in the atmosphere on an important share of days. Further details on the distribution of air quality appear in the Appendix.

3.2 Identifying the Effect of Smoke Exposure on Labor Market Outcomes

Our identification exploits variation in the annual, cumulative number of wildfire smoke days at the county level to identify the labor market effects of smoke exposure. We identify over 340,000 county-day smoke exposure events from 2006 to 2012, and we aggregate to the annual level to construct $Exposure_{ct}$, the number of days in year t to which county c was exposed to wildfire smoke. We then estimate the following regression equation:

$$Y_{ct} = \beta \cdot Exposure_{ct} + State_c \times Year_t + \alpha_c + X_{ct}\gamma + \varepsilon_{ct} \tag{3}$$

where Y_{ct} denotes labor market outcomes such as the log of per capita earnings in county c and year t. The primary coefficient of interest, β, can be interpreted as the effect of an additional day of wildfire smoke on annual earnings in the exposed county. We include county fixed effects, α_c, to control for time invariant differences in county labor market outcomes. Our smoke exposure effects are therefore identified using year-over-year variation in smoke exposure within the same county. In addition, we control for state-by-year effects to capture time-varying changes at the state level, such as the Great Recession.[24] X_{ct} includes time-varying weather controls that may independently affect labor market outcomes. These

[24]In the raw data, each additional day of smoke exposure in a county in a year is associated with 0.67 additional days of smoke exposure in the following year. Including county and state-by-year fixed effects reduces this association to a statistically insignificant 0.07 additional days of smoke. Thus, conditional on these controls, there is little year-over-year serial correlation in wildfire smoke exposure.

include the summed exposure to various levels of heat (in 9 bins), rain (6 bins), wind direction (6 bins) and wind speed (5 bins). To reflect the smoke exposure effect on a representative resident, we weight the regressions by county-annual population. To adjust for both within county and state-year autocorrelation, we two-way cluster standard errors at the county and the state-by-year level.

4 Results

This section presents our main results on the effect of wildfire smoke exposure on labor market outcomes. After presenting our baseline estimates (section 4.1), we then use both aggregate and individual level data to show that the effects are explained in part by reduced labor force participation and increased Social Security retirement income (section 4.2). We then document patterns in heterogeneity and connect them to other mechanisms (section 4.3).

4.1 Annual Earnings

Table 3 presents results from Equation 3 where the outcome is log of per capita labor income at the county level. We use earnings as measured by four distinct data sources, as well as a simple average of the four separate earnings measures. The results in the main text drop counties which experienced a wildfire in the same year.

Starting in Column 1, we find that each day of wildfire smoke exposure in a county reduces average annual wage and salary earnings reported to the IRS by 0.056 percent. Across the four measures of annual labor income, exposure to wildfire smoke significantly lowers the average annual income in a county by between 0.036 and 0.056 percent. We cannot reject the equality of the estimates from the four data sources. We report the average income estimates in the remaining columns, and also add leads and lags of smoke exposure; we lose one year of data with the addition of each lead and lag, somewhat reducing statistical power. The average effect across the four income measures is 0.044 percent, reported in column 5.

When we add the first lead and lag of smoke exposure in column 6, we find larger effects of 0.055 percent in the preceding year, and effects of 0.028 percent in the year of exposure. Multiplied by the average number of smoke days in the sample period, these estimates imply a total loss of 1.33 percent ($p < 0.01$) of national labor income in the United States each year as a consequence of wildfire smoke. The estimates are essentially unchanged in column 7, albeit with the loss of precision as the sample size shrinks. The leads are insignificant in both columns 6 and 7, as is the second lag of exposure in column 7.

We next expand on the earnings results in two figures. The linear functional form can be visually assessed in the residual plot in Figure 2. The figure reports the average residual in ten equally-sized bins. Most of the residuals fall close to the regression line, and the results do not appear to be driven by extreme smoke exposure events. Figure 3 reports more information on the effect of lags of smoke exposure to examine persistence, and leads as a placebo check. We estimate each lead and lag on its own to avoid dropping data, and plot estimates from all four data sources. The pattern of effects matches what we found in Table 3. Estimated on their own with the full sample, smoke exposure in year t has virtually the same effects as smoke in $t-1$. Further lags do not have signficant effects, even when we use the entire sample to estimate them. Looking at the leads, our strongest placebo test, we find no effect of smoke exposure that occurs in the future.

We perform several additional analyses and robustness checks, with detailed results reported in the Appendix. First, we replicate Table 3 using differing indicators for smoke exposure the county and surrounding counties on the same day to measure intensity. The results respond in the expected direction, with increasing effect sizes as neighboring counties experience more smoke exposure. We also test for an effect of exposure on the migration, measured as population size using the total number of tax exemptions claimed in an area, or directly by IRS county-to-county flows. By either measure, migration does not respond to an economically or statistically significant degree. In particular, we find small positive effects (i.e. wrong-signed) on the total population, and small negative coefficients on both

inflows and outflows.

4.2 Extensive Margin and Retirement Behavior

As discussed in the introduction, we hypothesize that the smoke effects should be strongest among older workers, and potentially generate losses associated with labor market transitions and retirements. The aggregate earnings analysis provides suggestive evidence, as the finding of significant effects of lagged exposure would be consistent with changes in participation or other reductions in attachment to the labor force.

We test these hypotheses in the following ways. First, we use the Bureau of Labor Statistics' Local Area Unemployment (LAU) Statistics to test explicitly for labor force participation responses to smoke exposure. We re-run our model at the monthly level, with the same set of fixed effects as above. Column 1 of Table 4 reports the results. We find that each day of wildfire smoke reduces employment in the county by 98 per million aged 16 and over in the month of exposure, which equates to a 0.25 percent decrease in LFP at average exposure levels. Effects are similar in magnitude in the month following exposure. Of course, this reductions in LFP need not exclusively reflect retirement, and based on age-specific health effects estimated in Schlenker and Walker (2016), it is possible that health responses occur below the usual retirement ages, as well.

Next, we use individual level data from the American Community Survey (ACS). Our empirical strategy here mirrors the one used in the above specification, except that smoke exposure is now defined at the PUMA level, with all regressions controlling flexibly for individual demographics such as age, gender, marital status, and education level. Column 2 of Table 4 reports that each day of smoke exposure reduces labor force participation (LFP) by 55 out of every million people aged 16 and over, consistent with a reduction in labor force participation.[25]

[25]The smaller effect may reflect measurement error resulting from our definition of smoke exposure based on exposure in the surrounding geographic units. PUMAs are constructed on a population, rather than a geographic, basis, and there are dramatically different sizes to PUMAs across the country.

Finally, we examine whether wildfire smoke shocks increase Social Security retirement benefit claiming. In this analysis, we use the same specifications as above applied to ZIP-code level data derived from Social Security Administration's administrative records. Table 4 contains results for SSA retirement beneficiaries (column 3) and benefits per claimant (column 4). We find that each day of smoke exposure increases the average number of retirement beneficiaries by 28 per million residents. Comparing this result to the preceding estimates, we estimate that a third or more of the change in participation and employment can be accounted for by new social security claimants.[26] Importantly, the SSA data is annual, so retirements must be shifted by a significant amount to be captured by this measure. In column 4 we test for a change in the composition of Social Security claimants, finding that the benefit per claimant rises 0.009 percent per day of smoke exposure. An increase in the average benefit can be explained by the fact the approximately 30 percent of individuals who claim retirement benefits shortly after they are first eligible, at age 62, are disproportionately poor. These individuals are "always-takers" in the treatment effects language, and as they are poorer than average, they are entitled to a smaller Social Security benefit. Thus, the individuals who respond to smoke exposure (the "compliers") are drawn from a selected, wealthier group. One implication of this finding is that the Social Security system provides insurance against some portion of the wildfire risk for this (relatively wealthier) group of individuals. Figure 4 depicts a residual plot of the effect of smoke exposure on claimants. As in the the earnings analysis, we cannot reject a linear relationship between days of smoke exposure and social security claimants.

A significant portion of the earnings results can be explained by the extensive margin and retirement effects. If those who leave the labor force earn average incomes, we can compare the 0.25 percent effect on LFP to the 1.33 percent effect on earnings, implying that 18.8% of the earnings effect is explained by LFP. This calculation is illustrative, and may understate

[26]The Social Security rules do not require claimants to quit work to claim benefits, and it is possible that some claimants do not show up as labor force dropouts. This suggests that a smaller share of labor force dropouts show up as claimants.

losses that occur due to these extensive margin effects. For example, we measure immediate declines in LFP, and lack the power to detect delayed response in retirement timing and participation.

4.3 Heterogeneity and Other Results

With our national variation, we can conduct heterogeneity analyses that have not been possible in previous studies of air pollution and labor markets. Patterns in heterogeneity provide suggestive evidence on underlying mechanisms.

Our strategy is to focus on the IRS data, as it can be disaggregated from county-level to ZIP codes, and divide ZIP codes into those with above- and below- median values of a number of characteristics: poverty, home value, fraction black, average PM_{10} (a measure of baseline pollution), fraction urban and unemployment (averaged over the sample period). We then re-run the earnings and social security claimant models with interactions between smoke exposure and indicators for the characteristics. We consider several robustness checks to address differing size of ZIP codes (which will introduce measurement error in the smoke exposure indicator for the largest ZIPs) and the correlation between our stratifying variables and other ZIP characteristics.

Table 5 reports the results of the earnings heterogeneity analysis. In the first row of results, we report results for the fraction urban. In ZIP codes with above average fraction urban, the effect size is -0.054 percent of labor income, while in areas with below average smoke exposure, there is no detectable effect. We test whether we can reject the equality of these coefficients, with p-values reported in the column 3. In this case, we strongly reject the equality of the effect in more and less urban areas, and conclude that response are concentrated in urban areas. Continuing down the panels, we find larger earnings losses in areas with lower home values and higher fraction black, and can reject the equality of the coefficients in both cases. Effects are also concentrated in high poverty ZIP codes, though the pattern is more muted. It is important to note that although earnings responses are

concentrated in these areas, they are not necessarily associated with these individual-level characteristics. For example, it could be that responses are largest for non-blacks living in areas with above-median concentrations of African-Americans. Despite this caveat, it is clear that smoke exposure has the largest effects in urban communities, far from the wildfires that produce the smoke. At the bottom of the table, we stratify ZIPs into above and below baseline PM_{10} measures in 2000-2005, before our sample period. We hypothesized that high pollution areas may be more adapted to smoke exposure, which could be reflected in a lower responsiveness to smoke. However, we find no evidence of a different effect size by baseline pollution exposure.

We conducted additional analyses of heterogeneity by industry, weekday vs weekend exposure, and an analysis of unemployment insurance claims.[27] The industry analysis is conducted using the County Business Patterns earnings data, which identifies earnings at the level of the industry level. Smoke has marginally larger effects in the professional services, real estate, and accommodation industries, with large, but statistically insignificant, negative point estimates in the construction and mining industries. There is no significant evidence of larger effects in industries that involve outdoor work, such as agriculture and construction. Effects in the accommodation industry may be consistent with reduced demand for services, but overall, the main conclusion we take from the industry analysis is that effects are reasonably dispersed across sectors. We find similar suggestive evidence of reduced demand for goods and service from larger effects on weekends ($p < 0.1$); however, increases in exposure due to time spent outdoors, or other changes in behavior, could contribute to the patterns we find. We find no evidence of larger reductions in the demand for goods and services resulting in layoffs or an increase in unemployment insurance claims in the CBP data.

[27] Detailed results are reported in appendix tables and figures.

5 Welfare

5.1 Air Pollution and Welfare

The preceding sections have demonstrated earnings losses and changes in labor force participation as a result of wildfire smoke exposure. Of course, the response of earnings does not necessarily reflect the response of individual or social welfare, which depends on the mechanisms which explain the decreased earnings. In particular, at least some portion of the lost earnings may be explained by increased leisure, for example, if workers stay home on high-pollution days. Similarly, if some workers are forced into early retirement by smoke-related illness, we would like to account for the replacement of market work with home production. Optimal policy should weigh the marginal cost of reduced pollution against the marginal damage to social welfare.

We can perform a simple welfare calculation building off the model in Section 1 and estimates in Table 3. To focus attention on the labor market costs, we separate the losses occurring through consumption and leisure, x and l, from direct losses arising from changes in health and amenities, s and c. We label utility from the first two terms as $U^{LM}(x, l)$. Considering a small change in pollution concentration, c, the loss in money-metric utility is

$$\frac{dW^{LM}}{dc} \equiv \frac{dU^{LM}/dc}{MU_x} = h\frac{dw}{dc} - w\frac{ds}{dc}.$$

The first term relates to the change in the wage, which leads to a welfare loss in proportion to labor supply, h. Intuitively, a lower wage directly subtracts dollars from consumption; then, hours change in response to reflect a re-optimization at this lower utility frontier. The second term reflects the direct loss of time due to illness, valued at the wage. We assume workers do not have sick leave, or if they do, that ds/dc reflects remunerated time away from work. We can then take the ratio of the welfare loss to the lost earnings, $dE/dc = d(wh)/dc$,

to calibrate the appropriate scaling of the earnings losses:

$$\frac{dW^{LM}/dc}{dE/dc} = \frac{1}{1 + \eta_{h,w} + \frac{w(\partial h/\partial c)}{dW/dc}} - \frac{w^0 \frac{ds}{dc}}{dE/dc}.$$

This equation reflects four responses that lead to lower earnings: lower wages, labor supply responses to this lower wage, avoidance behavior, and time lost due to illness. Only lower wages and time lost to illness reflect true utility loss, as increased leisure offset earnings losses due to labor supply responses and avoidance behavior.

Absent detailed data on time use and illness, we require some assumptions to calibrate the percentage of share of earnings losses that reflect true welfare costs. We focus on generating plausible upper and lower bounds, which turn out to be quite informative. First, avoidance behavior should only occur during the transitory shocks, and we set aside these reponses for our primary calculation. With this term removed, welfare losses lie between the wage response, $\frac{dE/dc}{1+\epsilon_{h,w}}$, and an upper bound of unity, the case when all earnings losses reflect time spent sick. Should welfare costs arise entirely due to changes in the wage, we can take a conservative value of the labor supply elasticity, $\eta_{h,w} = 0.5$ (drawing from Keane (2011), as in Dobkin et al. (2016)), and estimate that two-thirds of the earnings loss reflect true costs to the worker. This is our lower bound ratio of earnings losses that reflect true costs to welfare.

Applying these bounds to the estimates in Table 3, we conclude that the welfare losses working through labor market responses lie between $67 billion and $100 billion. Whether losses lie closer to the upper or lower bound depends on whether earnings responses reflect time spent away from work while ill, or lasting damage to labor market opportunities as a result of smoke exposure. These lasting damages show up as lower wages, but may reflect either reduced health capital following an acute smoke-induced illness (i.e. lower productivity of workers following the health shock), or worker transitions to lower-paid jobs induced by illness or labor demand effects. Costs associated with mortality, health care expenditures,

the disutility of smoke-induced illness, and other costs would then be added to this figure to reach the total damage done by wildfire smoke. Additional issues in the earnings welfare analysis are discussed in the appendix.

5.2 Comparison to Mortality Costs

To evaluate the importance of incorporating labor market effects into estimates of air pollution costs, we benchmark the welfare cost of lost earnings against that of premature deaths due to smoke exposure. We estimate mortality effects of wildfire smoke using a regression specification that closely mirrors Equation 3 from our earnings analysis. We regress the mortality rate M_{cmy} in county, c, month of the year, m, and year, y, on the number of days, $SmokeDays_{cmy}$, in which the county was exposed to wildfire smoke that month:

$$M_{cmy} = \beta \cdot SmokeDays_{cmy} + State_z \times Year_y + County_c \times Month_m + \alpha_c + X_{zt}\gamma + \varepsilon_{zy}. \quad (4)$$

The primary coefficient of interest is β, which describes the effect of an additional day of smoke exposure on mortality. We measure mortality as deaths per million in the month of smoke exposure. To account for delayed mortality effects as well as possible short-run mortality displacement (harvesting), we also estimate specifications where mortality is measured over 3-, and 6-month windows beginning with the month of exposure. To address the potential for serial correlation in smoke exposure, we control for lagged smoke exposure, as well as smoke exposure in the subsequent months when we extend the mortality window. We include the same weather controls, X_{zt}, as in Equation 3 and add fixed effects for county by month to control for seasonality in mortality. Standard errors are two-way clustered at the county and state by year levels.

Table 6 reports the results of the mortality analysis. Across all ages (column 1), mortality in the month of exposure increases by 0.31 deaths per million individuals (top panel), with effects growing to 1.183 deaths per million within three months of exposure (middle panel).

Both the 1- and 3-month mortality estimates are statistically significant at the 1 percent level. Extending the mortality window to six months following exposure (bottom panel) yields a positive but less-precisely measured mortality estimate of 1.023 deaths per million. Taken together, these estimates indicate medium-run mortality effects of smoke that level off between 3 to 6 months following smoke exposure.

Columns 2-5 of Table 6 report estimates of the mortality effect of smoke exposure separately by age group. We find mortality responses are concentrated among individuals aged 60 and older. Among this group, each day of smoke increases mortality by 2.1, 6.6, and 6.6 deaths per million within 1, 3, and 6 months of smoke exposure, respectively. The similarity in magnitude between the 3- and 6-month mortality estimates in this group suggests that the 3-month mortality estimates capture the extent of premature mortality from smoke, including potentially lagged effects.

To calculate the welfare cost of smoke mortality, we scale the age group-specific mortality effects by the average life expectancy among individuals in these groups and assume a \$100,000 value for each year of life lost, following Deschênes and Greenstone (2011).[28] If individuals who die from smoke exposure are less healthy than average among their age group, this approach will generate an upper bound on welfare cost of smoke mortality. Because of the small and statistically insignificant effects among younger age groups, we assume a negligible mortality cost among all age groups except the oldest group.

Following this approach, we calculate the welfare cost of smoke mortality by multiplying the mortality effect of smoke among the population aged 60 and older (6.609 deaths per million per day of smoke), the average life expectancy among this population (13.8 years of life per death), the size of this population in millions (59.0, per 2012 U.S. Census), the average number of smoke days per year (16.0), and the value of a life year (\$100,000 per life year lost). This generates an estimate of \$8.63 billion in mortality costs due to wildfire

[28]We calculate average life expectancy among each age group from the 2014 period life table for the Social Security area population, downloaded from https://www.ssa.gov/oact/STATS/table4c6.html#ss on September 8, 2017.

smoke each year.

A key feature of the analysis is that we use the same measured variation in both the earnings and mortality analysis. The estimates from the labor market can then be directly compared to the mortality costs. We find that mortality costs are approximately one-ninth of the lost labor market earnings. Taking our lower bound on lost welfare of $66.5 billion, the labor market costs impose a burden that is 7.7 times as large as the mortality cost; the labor market costs would rise to 11.6 times the mortality cost at the upper bound. These welfare calculations demonstrate that lost labor market earnings represent a source of welfare losses that should be considered as large or larger than mortality costs, which are usually thought to comprise the majority of health costs. A full welfare accounting would consider elements such as medical costs, losses to firms, the deadweight loss of additional tax revenue required to make Social Security payments, and adaptive and defensive investments. However, the literature has traditionally focused on mortality as the primary driver of costs, and the inclusion of these elements would not alter the primary conclusion, that labor market responses impose an important, or even primary, share of the welfare costs of wildfire smoke.

6 Discussion and Conclusion

Wildfires cause severe damage to the areas they burn, destroying homes, property, and threatening lives. Somewhat less obviously, wildfires produce a harmful and prevalent source of air pollution, with diffuse effects experienced by most of the US population at some point each year. We use the variation in wildfire smoke exposure within regions and between years to estimate its aggregate impacts on total earnings, labor force participation, and Social Security retirement benefit claims. We find smoke exposure causes a significant decrease in earnings, associated with decreased labor force participation and increases in Social Security retirement income. While previous studies have emphasized worker productivity effects and sick-leave, it is not clear who bears the incidence of output lost due to these responses.

With a nationally-representative study and annual outcomes, we document that labor bears significant income losses in response to transient air pollution events. When we compare the earnings losses to the welfare costs resulting from increased mortality, we find that earnings losses impose significantly larger costs than mortality.

The findings in this paper have broad implications for environmental policy and the growing literature on the labor market effects of air pollution. The WHO, OECD, World Bank, and EPA consider damages arising from lost labor market hours and earnings to comprise an important secondary source of welfare loss to air pollution that is considerably smaller than the health impacts, of which mortality dominates. However, the methods used to estimate these labor-market related losses ignore behavioral responses and other mechanisms documented in the literature. We provide the first quasi-experimental evidence on the effect of air pollution events on labor markets at a national scale, and find that labor market effects are far more important than is suggested by previous studies. Links from air pollution to the labor market imply the employment-reducing effects of environmental regulation are at least partially offset by gains to workers along other dimensions.[29] Although wildfire smoke has a different chemical composition than industrial pollution or car exhaust, smoke exposure results in meaningful increases in EPA-monitored pollutants. Wildfire smoke more closely resembles the exhaust from the burning of biomass for fuel or field-clearing, a common source of air pollution in developing countries. As more detailed data emerges over the coming years, it will hopefully be possible to disentangle the role of various mechanisms and individual pollutants.

We conclude with a discussion of the implications of our findings for the study of wildfire. First, our findings imply large externalities in land use and fire management that call for greater coordination of policy efforts. Second, in a very basic sense, fire policy should (re-)focus on preventing smoke-producing wildfires from starting and spreading; the narrow goal of defending land and property exposed to fire damage should not be allowed to sub-

[29] Schwartz and Repetto (2000) and Williams III (2003) discuss how health effects of pollution impact optimal taxation of pollutants.

sume fire management budgets. Fires generating large smoke plumes that may reach urban centers should be prioritized over fires far from or downwind of population centers. Forest fires consume denser biomass than prairie fires, therefore generate more and thicker smoke, and should be prioritized. Third, fuel reduction and the use of prescribed burning (fires set intentionally to remove fuel) should likely expand, though they should be set to take into account wind patterns to avoid population exposure. And finally, estimates of the marginal cost of firefighting and prevention—already sorely lacking in the literature—should consider both the cost of reducing acreage burned, and the cost of reducing population smoke exposure. While fires and smoke are inevitable, planning and policy can mitigate the damage done.

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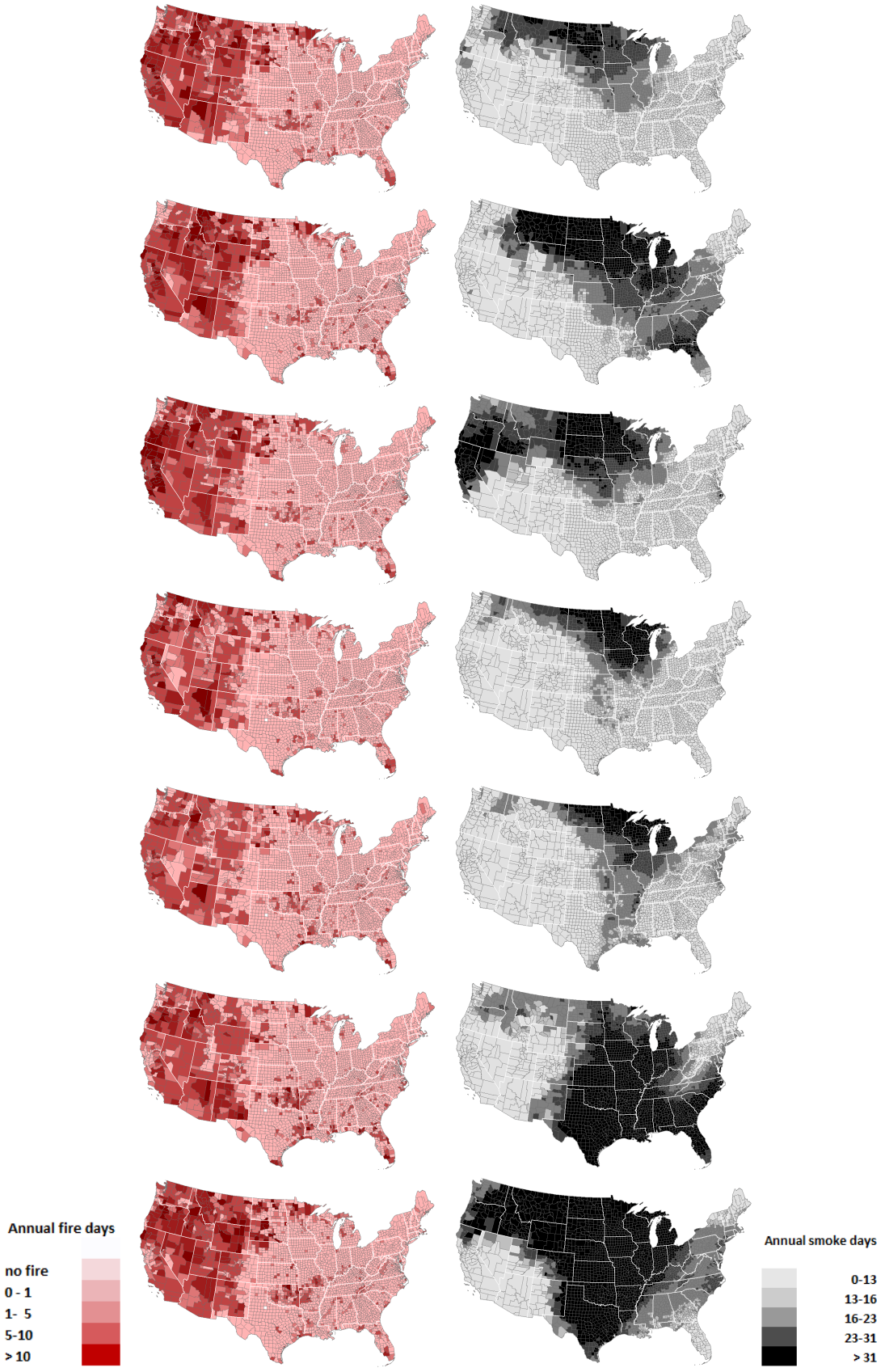
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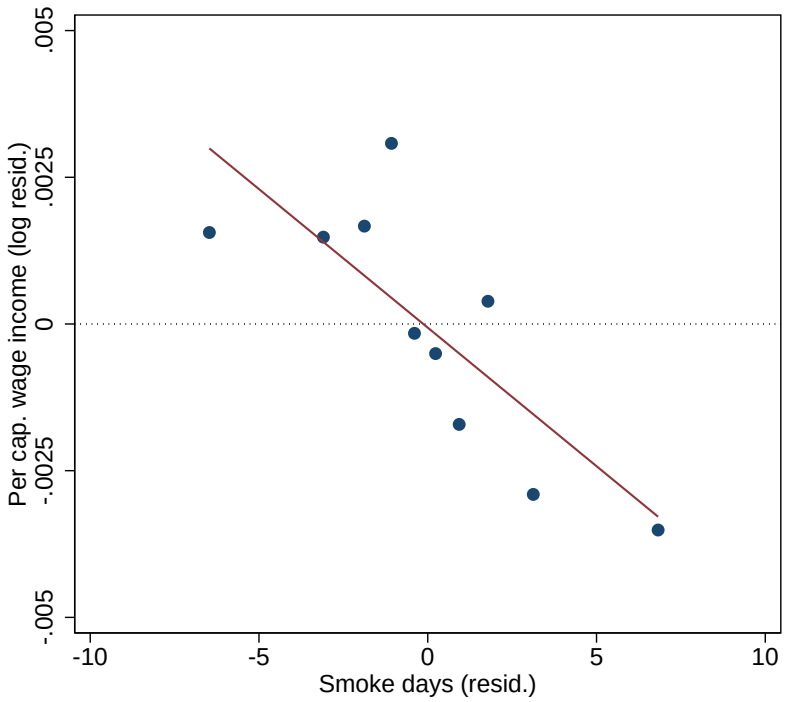
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Figure 1: County Annual Wildfire and Smoke Exposure 2006 (top panel) - 2012 (bottom panel)



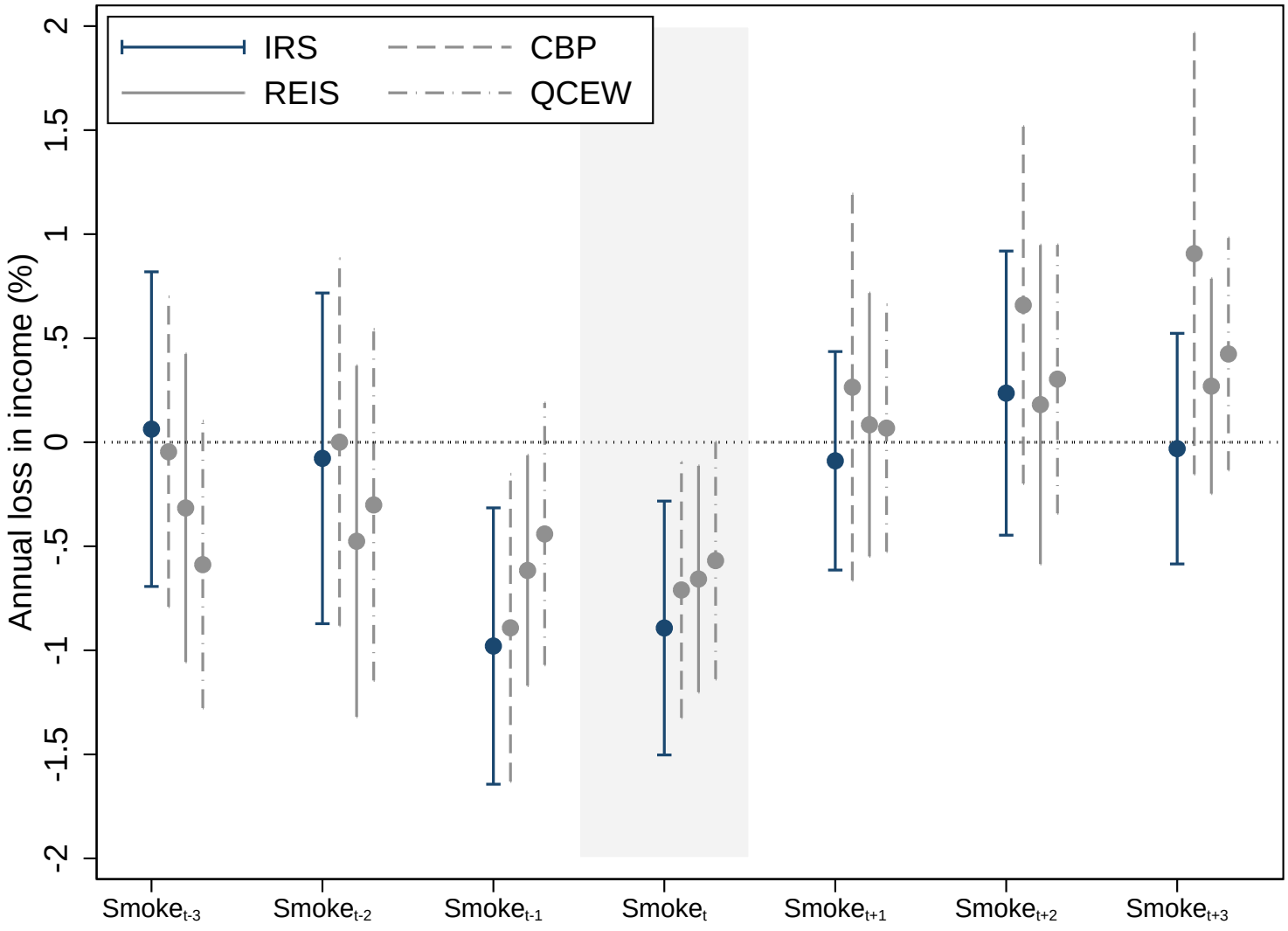
Notes: This figure plots year-by-year county level average annual days of wildfire (left) and days of smoke exposure (right) for the lower 48 states, from top panel (year 2006) to bottom panel (year 2012).

Figure 2: Effects of Smoke Days on Wage Income: Residualized Plot



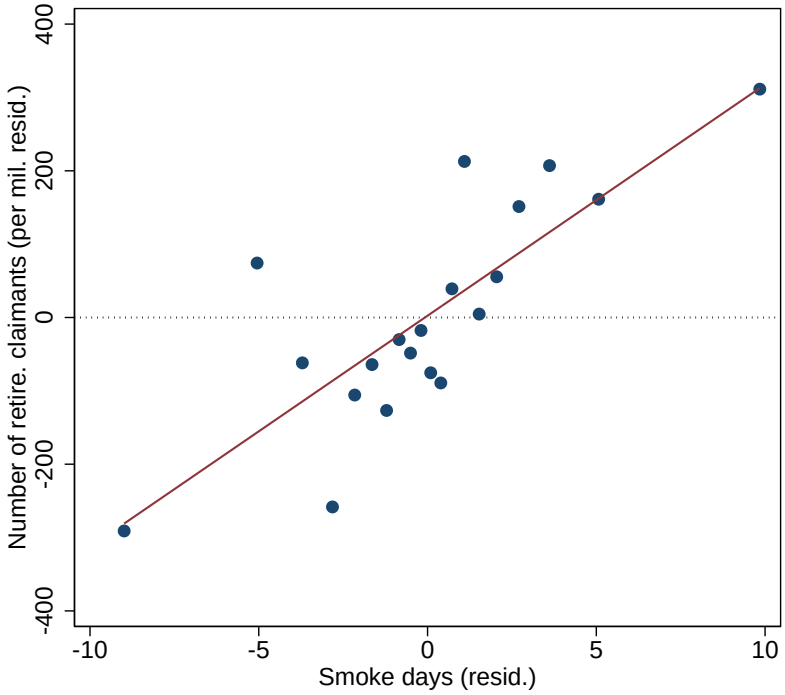
Notes: Graph presents average residualized log per capita wage income by equal bins of residualized annual smoke days. The source of wage income measure is the average between county level IRS, CBP, REIS, and QCEW. Regression includes state×year fixed effects and county fixed effects. Weather controls include 9 daily temperature bins, 6 annual precipitation bins, 6 daily wind direction bins, and 5 annual wind speed bins. Regressions exclude counties with wildfire in the year.

Figure 3: Effects of Smoke Days on Earnings: Placebo Specification



Notes: Each range plot item shows results from a separate regression where independent variable is number of smoke days in year $t+k$ ($k=-3,-2,-1,0,1,2,3$). Each group of range plot items uses a different source of earnings measure, as indicated by the graph legend. Exposure is measured by number of days a county is entirely exposed to smoke, divided by the average annual number of smoke days. Regressions control for county fixed effects, state $\times$ year fixed effects. Weather controls include 9 daily temperature bins, 6 annual precipitation bins, 6 daily wind direction bins, and 5 annual wind speed bins. Regressions exclude counties with wildfire in the year. Standard errors are two-way clustered at the county level and the state $\times$ year level.

Figure 4: Effects of Smoke Days on Social Security Recipients



Notes: Graph presents residualized retirement claimants by equal bins of residualized annual smoke days. Regression includes ZIP Code fixed effects and state×year fixed effects. Weather controls include 9 daily temperature bins, 6 annual precipitation bins, 6 daily wind direction bins, and 5 annual wind speed bins. Regressions are weighted by ZIP Code level population. Regressions exclude counties with wildfire in the year.

Table 1: Summary Statistics

	(1) Mean	(2) Std. dev.	(3) N (counties)
Daily distance to wildfire (miles)	877.4	591.9	3,090
Daily distance to wildfire on smoke days (miles)	386.4	431.2	3,090
Annual smoke exposure (days)	16.00	15.78	3,090
Per cap. wage income (IRS/CBP/REIS/QCEW, 2010$)	24,266	10,679	3,091
Per cap. wage income (IRS, 2010$)	20,876	10,716	29,677 (ZIP Codes)
Retirement claimants (per million)	105,417	46,314	29,252 (ZIP Codes)
Per claimant retirement benefits (2010$)	14,172	1,474	29,441 (ZIP Codes)

Notes: Distance to fire is computed as daily distance to the nearest wildfire. "Annal smoke exposure" is average county-level annual number of smoke days. "Per cap. wage income (IRS/CBP/REIS/QCEW, 2010$)" is the average county-level wage income measure using combined IRS, CBP, REIS, and QCEW data. These statistics are weighted by county population. ZIP Code level statistics are weighted by IRS tax exemptions (per capita wage income, retirement claimants), or retirement claimants (per claimant retirement benefits).

Table 2: Effect of Wildfire Smoke on EPA Criteria Pollutants

	(1) $PM_{2.5}$	(2) PM_{10}	(3) O_3	(4) CO	(5) NO_2	(6) SO_2
Unit of measure	$\mu g/m^3$	$\mu g/m^3$	ppb	ppb	ppm	ppm
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
Panel B. Annual Effect						
Exposure	0.219***	1.061***	0.192	0.271	-0.120	0.072
	(0.077)	(0.231)	(0.127)	(1.045)	(0.144)	(0.078)
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

Notes: Each cell corresponds to a separate regression. Panel A presents the effect of a smoke day on air pollution on that day. Dependent variable is daily pollution concentration and independent variable is county-daily smoke exposure dummy (*Smoke Day*). All daily regressions control for county×day-of-year fixed effects, state×day-of-year fixed effects, day-of-week fixed effects, 3-day leads and lags of smoke, 10-degree daily temperature bins, and quadratic daily precipitation. Standard errors are two-way clustered at the county and the date level. Panel B presents the effect of annual smoke exposure on annual air pollution. Dependent variable is annual pollution concentration and independent variable is county-annual number of smoke days in a year divided by the average annual number of smoke days (*Exposure*). All regressions include county fixed effects and state×year fixed effects. Weather controls include 9 daily temperature bins, 6 annual precipitation bins, 6 daily wind direction bins, and 5 annual wind speed bins. Standard errors are two-way clustered at the county and the state×year level.

Table 3: Annual Wage Income Effect 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		
Exposure (lead)						-0.003	-0.014
						(0.016)	(0.010)
Exposure (current)	-0.056***	-0.044**	-0.041**	-0.036*	-0.044***	-0.028**	-0.028*
	(0.019)	(0.020)	(0.017)	(0.018)	(0.015)	(0.014)	(0.017)
Exposure (1^{st} lag)						-0.055**	-0.046*
						(0.022)	(0.025)
Exposure (2^{nd} lag)							-0.010
							(0.028)
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

Notes: Table shows % loss of annual wage income due to an additional day of wildfire smoke exposure. 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. *Exposure* counts number of days a county is exposed to wildfire smoke. All regressions include county fixed effects and state×year fixed effects. Weather controls include 9 daily temperature bins, 6 annual precipitation bins, 6 daily wind direction bins, and 5 annual wind speed bins. Regressions are weighted by county population. All regressions exclude counties with wildfires in the year. Standard errors are two-way clustered at the county and the state×year level.

Table 4: Annual LFP and Retirement Effects of Wildfire Smoke

Source of measure:	BLS LAU	ACS	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. × 100)
Exposure	-97.6***	-54.5	27.6*	0.009**
	(34.1)	(57.5)	(15.2)	(0.004)
Mean dep. var.	625,837	644,202	105,149	0.155
ZIP Code/county/PUMA level?	county	PUMA	ZIP Code	ZIP Code
Annual/monthly frequency?	monthly	annual	annual	annual
N	244,202	11,072,008	187,468	188,522
N (ZIP Codes/county/PUMA)	2,993	2,051	28,376	28,554

Notes: Each cell corresponds to a separate regression. *Exposure* counts number of days a county (column 1) / PUMA (column 2) / ZIP Code (columns 3-4) is exposed to wildfire smoke in a month (column 2) or year (column 2, column 3, column 4). All regressions include geographic fixed effects and state×year fixed effects. Weather controls include 9 daily temperature bins, 6 annual precipitation bins, 6 daily wind direction bins, and 5 annual wind speed bins. Regressions are weighted by population aged 16 and over at the county (column 1), census individual weights (column 2), population at the ZIP Code (column 3), and retirement claimants at the ZIP Code (column 4). Standard errors are two-way clustered at the geographic area and the state×year (column 1-4) level. The ACS regression includes individuals aged 16 and over from 2007-2011 samples.

Table 5: Heterogeneous Earnings Effects of Wildfire Smoke

Dep. var.:	Log per cap. wage income (IRS ZIP Code level) coeff. × 100			
	$\geq$ *median*	$<$ *median*	p value	N
Frac. urban	-0.054***	0.015	0.000	176,898
	(0.013)	(0.013)		
Poverty	-0.060***	-0.041**	0.036	176,610
	(0.014)	(0.013)		
Low home value	-0.068***	-0.044***	0.007	175,715
	(0.014)	(0.013)		
Frac. black	-0.059***	0.011	0.000	176,822
	(0.013)	(0.011)		
Avg. PM_{10}	-0.038***	-0.041***	0.756	87,983
	(0.014)	(0.012)		

Notes: Each row corresponds to smoke exposure interacted with above and below median characteristics indicated by row names. Characteristics definitions are: state-year unemployment rates (row 1), ZIP Code poverty rate estimates from ACS 2007-2011 (row 2), ZIP Code median home value estimates from ACS 2007-2011 (row 3), ZIP Code fraction of African American population estimates from ACS 2007-2011 (row 4), ZIP Code fraction of urban population estimates from ACS 2007-2011 (column 5), and ZIP Code 2000-2005 average PM_{10} level (row 6). Dependent variable is number of days a ZIP Code is exposed to wildfire smoke. Regressions exclude ZIP Code-year that ever had wildfires according to the fire register data. All regressions include ZIP Code fixed effects and state×year fixed effects. Weather controls include 9 daily temperature bins, 6 annual precipitation bins, 6 daily wind direction bins, and 5 annual wind speed bins. Regressions are weighted by ZIP Code-annual number of tax exemptions. Standard errors are two-way clustered at the ZIP Code and the state×year level.

Table 6: Mortality Effect 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	0.306***	0.012	0.085	0.038	2.105***
	(0.096)	(0.056)	(0.065)	(0.139)	(0.667)
Mean dep. var.	669.7	48.2	91.8	358.2	2,926.4
3-month mortality	1.183***	-0.038	0.078	0.282	6.639***
	(0.302)	(0.101)	(0.111)	(0.263)	(1.346)
Mean dep. var.	2,006.3	144.8	275.7	1,074.1	8,779.9
6-month mortality	1.023*	0.151	-0.109	-0.311	6.609***
	(0.609)	(0.148)	(0.206)	(0.472)	(2.380)
Mean dep. var.	4,011.2	289.6	551.8	2,148.7	17,599.6

Notes: Number of county×month observations ranges from 229,910 (6-month mortality specification) to 244,316 (1-month mortality specification). 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. All regressions include county×month-of-year fixed effects and state×year fixed effects. Weather controls include 9 daily temperature bins, 6 monthly precipitation bins, 6 daily wind directions bins, and 5 monthly wind speed bins. 3- and 6-month mortality regression control additionally for number of smoke days in the look-ahead window. Regressions are weighted by county-year population in the relevant age groups. Standard errors are two-way clustered at the county and the state×year level.

A Online Appendix

A.1 Distribution of Air Pollution on Exposure Days

The analysis in the main text uses an indicators for smoke exposure as the treatment. We also describe the effect of smoke exposure on the average levels of daily pollution, and the contribution of smoke to annual pollution. In this section, we discuss the changes in the distribution of daily air pollution that is generated by smoke exposure events. In particular, we characterize the duration and intensity of smoke exposure using two figures. This analysis demonstrates that our smoke exposure indicator captures meaningful variation that is not driven by extreme events, does not overwhelming reflect high atmosphere smoke.

Figure A.3 shows daily level pollution event studies for more than 5.4 million ZIP-day smoke events from 2006 to 2012. To construct this figure, we first construct percentiles of smoke exposure days based on the level of $PM_{2.5}$ measured on the day of exposure; this level is reported on day 0 of the figure for the 5th, 25th, 50th, 75th and 95 percentiles above the mean of pollution in that ZIP code. We then plot $PM_{2.5}$ levels for 20 days before and after the day of exposure. Other days within the window may or may not be coded as smoke exposure days. From the graph it can be seen that an average smoke driven air pollution surge largely dissipates less than 5 days following the shock, and the longest and largest events rarely last more than 10 days. The transient nature of the shock makes it unlikely they cause permanent shifts in local economic activity.

Figure A.2 plots the residuals of daily smoke exposure against residual $PM_{2.5}$ measures. Together, this represents the unexpected air pollution on the days with unexpected smoke. We first regress the smoke indicator on county by day-of-year fixed effects, day-of-week fixed effects, 3 days of leads and lags of the smoke indicator, 10-degree daily temperature bins, 60-degree daily wind direction bins, quadratic daily wind speed and quadratic daily precipitation. We then create 20 equally-sized bins of the residuals of the smoke indicator. Higher values represent unexpected smoke days. Within each bin, we plot the 10th, 25th, 50th, 75th and 90th percentiles of $PM_{2.5}$, residualized in the same manner. These represent unexpected pollution. Two results emerge. First, the variation is nearly constant across the distribution. Our main estimate in Table2 shows that a smoke exposure day increase pollution by $2.19 \mu g/m^3$, which is close to the slope within each percentile. Second, the data is well-characterized by a linear model, and hence, by average effects. Days with unexpected smoke exposure do not show dramatically different patterns than the average.

A.2 Additional Welfare Analysis: Other Margins and Tax Externalities

We assume several responses are small enough to ignore in the primary welfare calibration. In particular, incorporating avoidance behavior responses would reduce the share of earnings that would represent welfare loss. Similarly, we have little information on the incidence of concurrent productivity effects on workers; as productivity effects would show up as lower wages, these would increase the welfare loss.

An alternative and extreme lower bound on the share of earnings offset by other sources of utility could be calculated by considering the externality on the tax system. Avoidance behaviors, as well as labor supply response to a lower wage, reflect individual optimization, and therefore do not incorporate the value of lost tax revenue. These externalities on the tax system would increase the welfare response in proportion to the average marginal tax rate on lost earnings. To be specific, consider the social welfare function of an economy with N-identical agents, with an after-tax wage in place of the previous wage rate, the marginal utility of private consumption normalized to 1, and social value of government expenditures equal to σ:

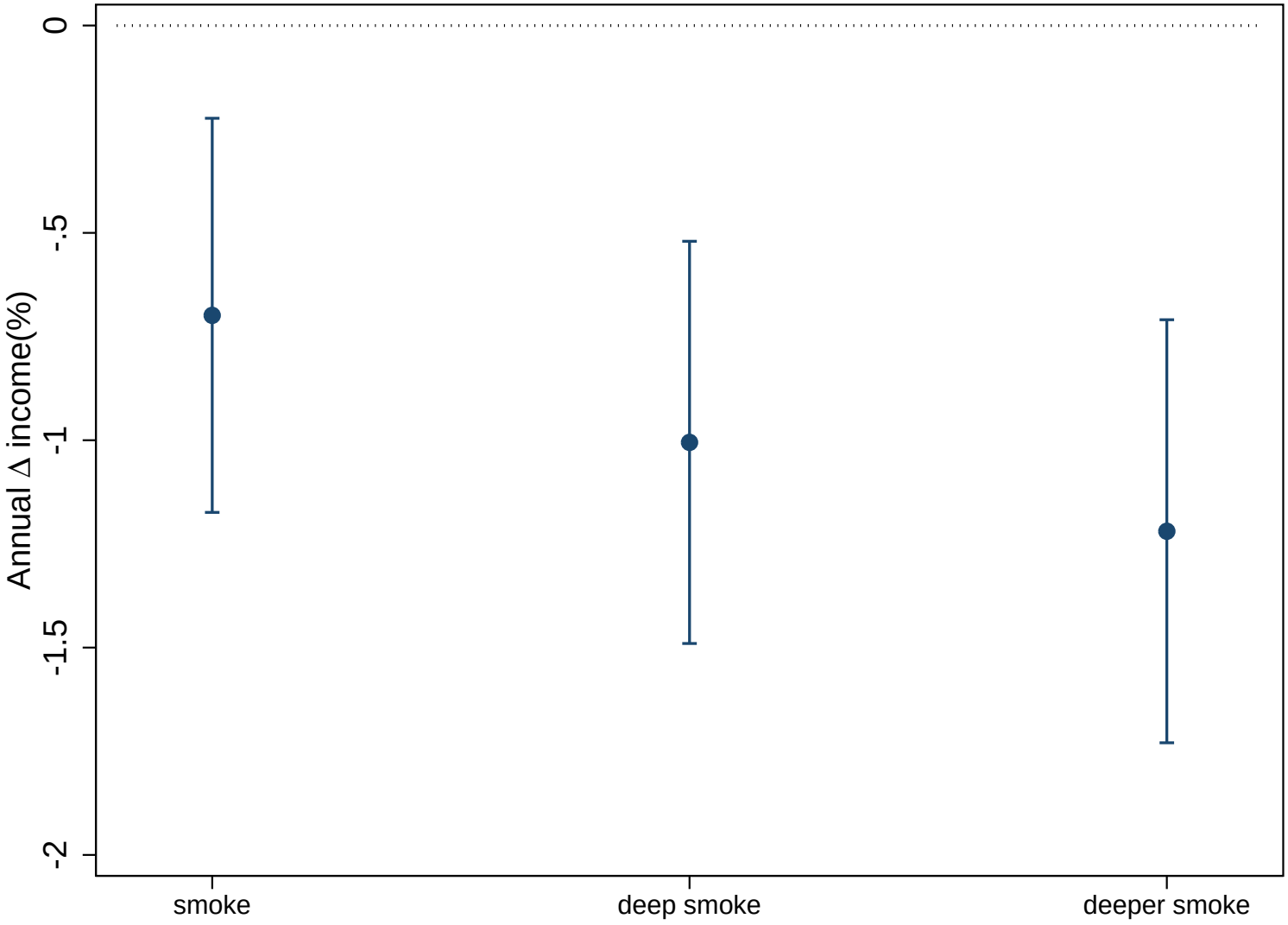
$$W/N = \sigma twh + argmax_{X,h} U(X, h((1-t)w, s, c), s, c)$$

Agents optimize utility by the choice of consumption and labor supply, but do not consider the effect of lost earnings on the tax system. In an optimal tax and spending system, this lost tax revenue should be valued at the deadweight loss of raising additional tax revenue, which will be above the value of private consumption. Applying a tax rate of 25%, a conservative value that is close to the average tax rate in the US, and $\sigma = 1$, would have us increase our

above lower bound from two-thirds to above three-quarters (Tax Foundation, 2014). Even in the implausible case where all earnings responses reflect avoidance behavior, the lower bound on welfare losses would not fall below 25% of the earnings losses, $25 billion.

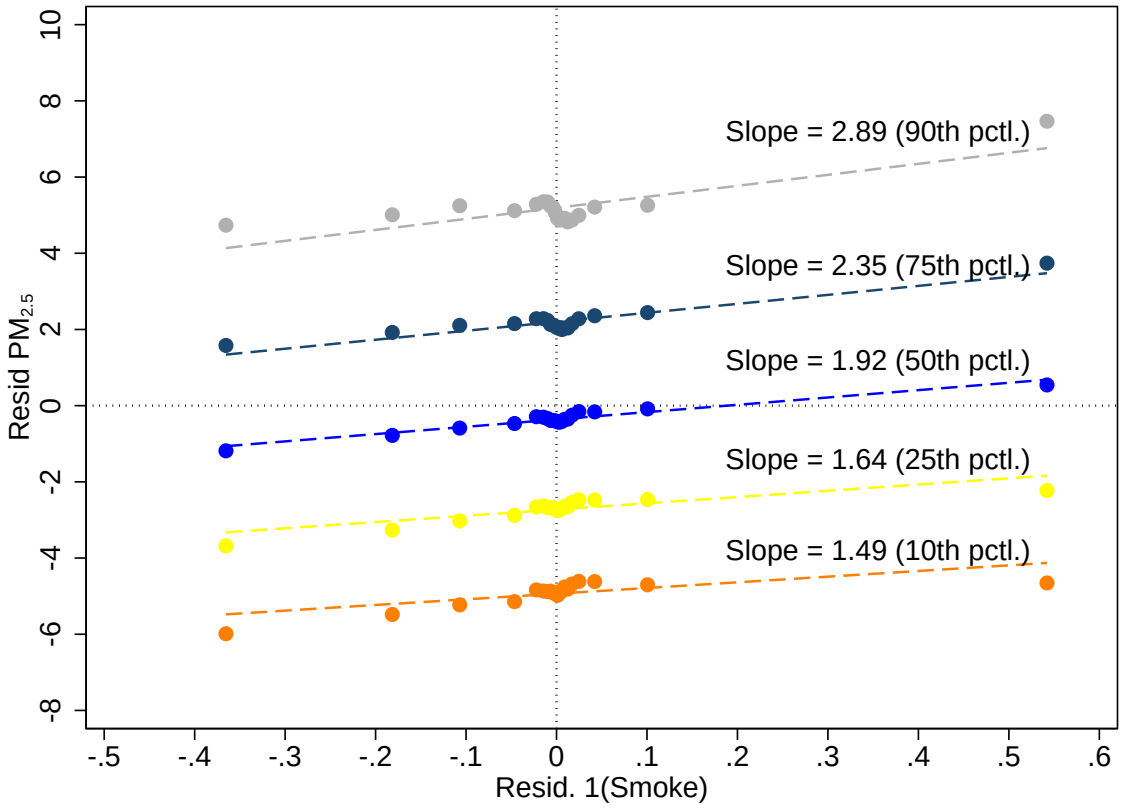
Online Appendix Figures

Figure A.1: Annual Wage Income Effect of Wildfire Smoke: Intensity of Exposure



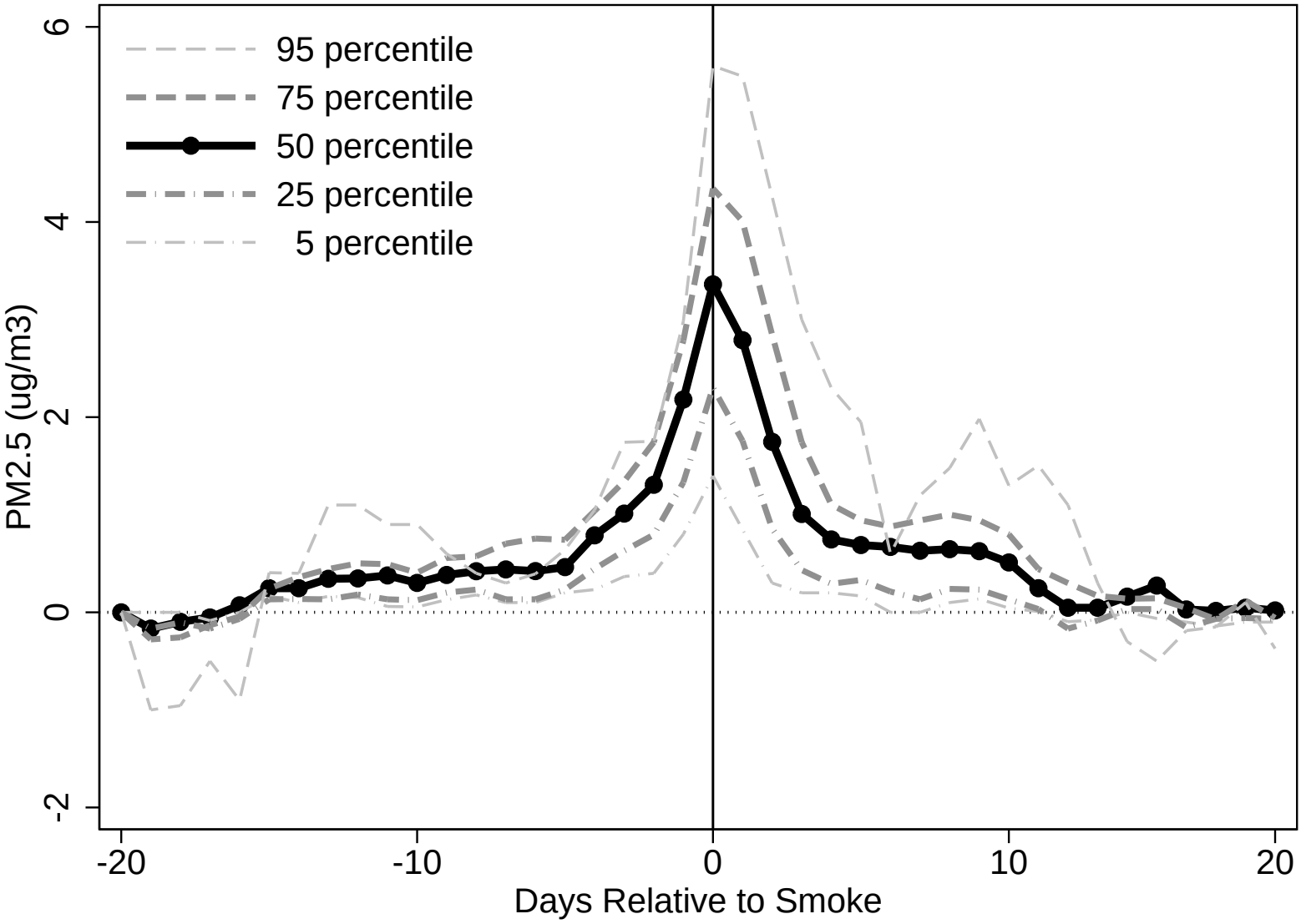
Notes: Each range plot item shows results from a separate regression using IRS ZIP Code level earnings data. Graph shows % loss of annual wage income due to wildfire smoke exposure. Dependent variables are "smoke" = number of days a ZIP Code intersects a smoke plume, regardless of neighbor ZIP Codes' exposure; "deep smoke" = number of days exposed when all neighbor ZIP Codes are exposed, our primary outcome measure in the paper; "deeper smoke" = number of deep smoke days, when all neighbor ZIP Codes are deeply exposed. All dependent variables are divided the average annual number of smoke days. All regressions include ZIP Code fixed effects and state×year fixed effects. Weather controls include 9 daily temperature bins, 6 annual precipitation bins, 6 daily wind direction bins, and 5 annual wind speed bins. Regressions are weighted by ZIP Code-annual number of tax exemptions. Standard errors are two-way clustered at the ZIP Code and the state×year level.

Figure A.2: Residual Plot: $PM_{2.5}$ vs. Smoke



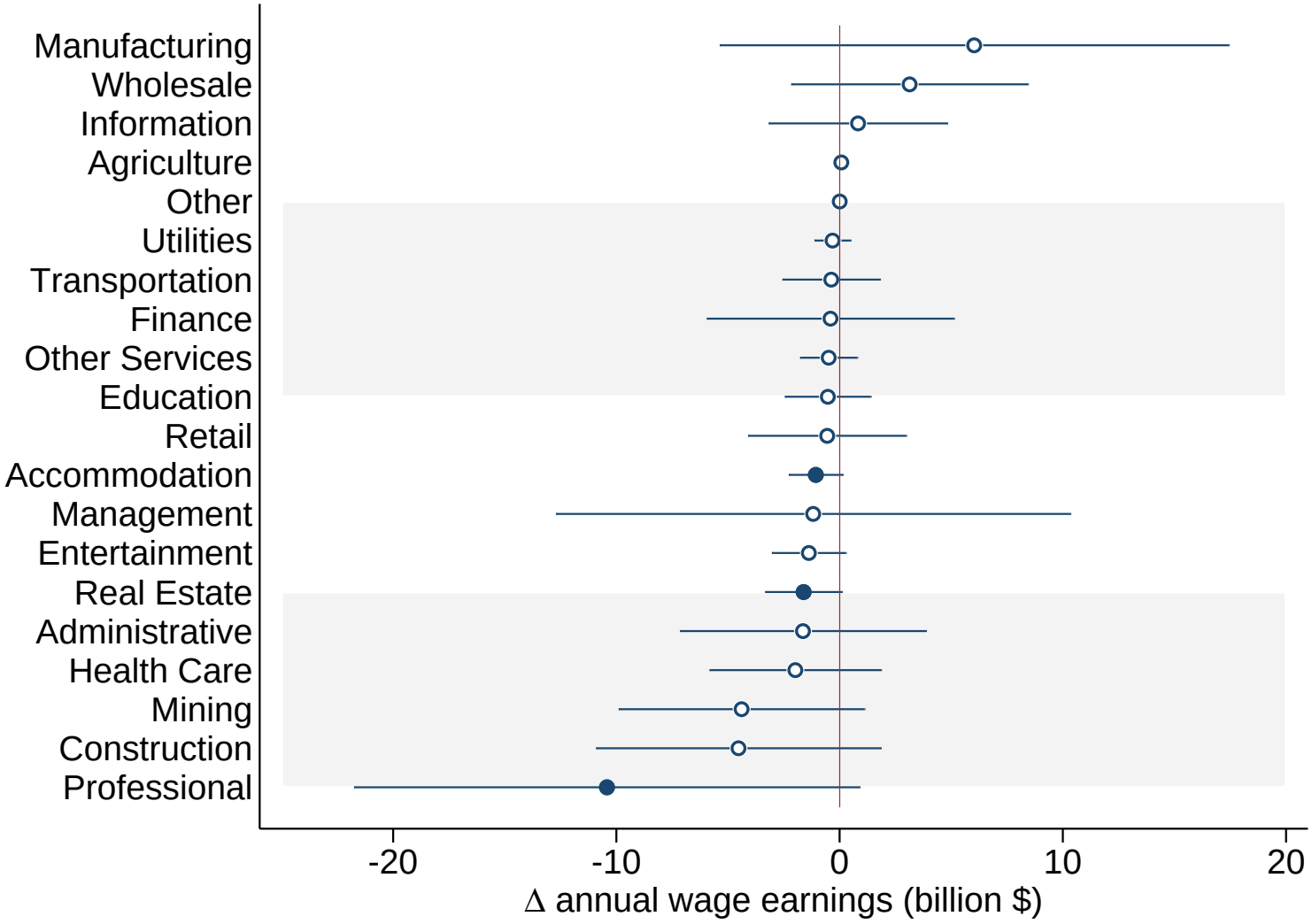
Notes: Graph shows percentiles of residualized $PM_{2.5}$ ($\mu g/m^3$) by 20 equal bins of residualized smoke indicator. Regressions control for county×day-of-year fixed effects, state×day-of-year fixed effects, day-of-week fixed effects, 3-day leads and lags of smoke, 10-degree daily temperature bins, 60-degree daily wind direction bins, quadratic daily wind speed and quadratic daily precipitation.

Figure A.3: Distribution of Intensity of Smoke-Induced Air Pollution Events



Notes: This figure plots the distribution of $PM_{2.5}$ concentration for each day within a 40-day window around 4 million smoke shock events. Event day 0 corresponds to the smoke exposure day, and event day -20 is normalized to 0. Average daily $PM_{2.5}$ concentration is about 11 $\mu g/m^3$.

Figure A.4: Heterogeneous Effects of Smoke on Labor Earnings by Industry



Notes: Industry-specific effects of smoke on county level payroll income using data from the County Business Patterns. Figure presents coefficients obtained from a single regression where smoke effect is allowed to vary by 2-digits NAICS, scaled by average annual total industry-wise payroll income during the 2006-2012 period. Regression controls for NAICS×county fixed effects and NAICS×state×year fixed effects. Filled in markers denote significance at $p<0.1$; bars represent 95% confidence intervals.

A.3 Online Appendix Tables

Table A.1: Annual Wage Income Effect of Wildfire Smoke: Including Fire Counties

Dep. var.: Log per capita wage income (coeff. × 100)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Data source:	IRS	CBP	REIS	QCEW	Average		
Exposure (lead)						-0.020	-0.019
						(0.016)	(0.012)
Exposure (current)	-0.047***	-0.0373**	-0.031**	-0.029**	-0.034***	-0.036***	-0.041***
	(0.012)	(0.015)	(0.013)	(0.013)	(0.011)	(0.012)	(0.014)
Exposure (1^{st} lag)						-0.024	-0.025
						(0.021)	(0.021)
Exposure (2^{nd} lag)							-0.010
							(0.006)
N	20,511	20,302	20,326	20,578	20,578	14,705	11,761
N (counties)	2,993	2,991	2,958	2,994	2,994	2,986	2,981

Notes: Table shows % loss of annual wage income due to an additional day of wildfire smoke exposure. 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. *Exposure* counts number of days a county is exposed to wildfire smoke. All regressions include county fixed effects and state×year fixed effects. Weather controls include 9 daily temperature bins, 6 annual precipitation bins, 6 daily wind direction bins, and 5 annual wind speed bins. Regressions are weighted by county population. Standard errors are two-way clustered at the county and the state×year level.

Table A.2: 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

Notes: Table shows annual % population migration effect due to wildfire smoke exposure. Each column corresponds to a separate regression which uses a different county×year measure of migration. Column 1 uses number of tax exemptions. Column 2 uses (log) number of out-migrants per capita. Column 3 uses (log) number of in-migrants per capita. Both out- and in-migrants flows have a mean of roughly 46 migrants per 1,000 individuals per county × year. All migration measures are derived from IRS SOI. *Exposure* counts number of days a county is exposed to wildfire smoke, divided the average annual number of smoke days. All regressions include county fixed effects and state×year fixed effects. Weather controls include 9 daily temperature bins, 6 annual precipitation bins, 6 daily wind direction bins, and 5 annual wind speed bins. All regressions exclude counties with wildfires in the year. Standard errors are two-way clustered at the county and the state×year level.

Table A.3: Labor Demand Effect of Wildfire Smoke

	(1)	(2)	(3)	(4)
	Log number of employees (coeff. × 100)		Log per capita wage income (coeff. × 100)	
Exposure	0.026	-0.018		
	(0.033)	(0.369)		
Exposure (weekdays)			-0.367	-0.462
			(0.385)	(0.420)
Exposure (weekends)			-1.064	-1.339
			(0.799)	(0.841)
Exclude fire ZIP Codes		✓		✓
N	168,425	160,886	185,499	177,263
N (ZIP Codes)	27,529	27,264	28,967	28,687

Notes: Each column corresponds to a separate regression. *Exposure* counts number of days a ZIP Code is exposed to wildfire smoke, divided by the average annual number of smoke days. All regressions include ZIP Code fixed effects and state×year fixed effects. Weather controls include 9 daily temperature bins, 6 annual precipitation bins, 6 daily wind direction bins, and 5 annual wind speed bins. Regressions are weighted by ZIP Code-annual number of tax exemptions. Standard errors are two-way clustered at the ZIP Code and the state×year level.

Table A.4: Effect of Wildfire Smoke: Other Income Measures

Dependent variable: Log per capita IRS income (coeff. × 100)						
	(1)	(2)	(3)	(4)	(5)	(6)
	AGI	Wage inc.	Capital	Interest	Dividend	Other inc.
Panel A. Independent variable: smoke (days/22)						
Exposure	-0.559**	-0.699***	2.859	0.183	-1.799	-0.326
	(0.260)	(0.242)	(2.064)	(1.025)	(1.158)	(0.472)
Panel B. Independent variable: "Deep" smoke (days/20)						
Exposure	-0.960***	-1.005***	1.421	-0.214	-0.232	-0.617
	(0.248)	(0.247)	(2.264)	(0.850)	(1.068)	(0.480)
N	177,272	177,263	162,973	176,671	171,119	177,020
N (ZIP Codes)	28,695	28,687	27,084	28,353	27,240	28,627

Notes: Table shows % loss of annual wage income due to wildfire smoke exposure. Each cell corresponds to a separate regression. *Other inc.* is the difference between adjusted gross income (AGI) and the summation of wage, capital interest, dividend income. *Exposure* counts number of days a ZIP Code is exposed to wildfire smoke, divided by the average annual number of smoke days. "Deep" smoke counts exposure when a ZIP Code is exposed to wildfire smoke when all its neighbor ZIP Codes are exposed, divided by the average annual number of deep smoke days. Regressions exclude all ZIP Code-year that ever had wildfires according to the fire register data. All regressions include ZIP Code fixed effects and state×year fixed effects. Weather controls include 9 daily temperature bins, 6 annual precipitation bins, 6 daily wind direction bins, and 5 annual wind speed bins. Regressions are weighted by ZIP Code-annual number of tax exemptions. Standard errors are two-way clustered at the ZIP Code and the state×year level.

Table A.5: Heterogeneous $PM_{2.5}$ Effects of Wildfire Smoke

Dependent variable: $PM_{2.5}$ concentration (ug/m^3)							
	smoke effect			Exclude	Interact		
	$\geq$ *median*	$<$ *median*	p value	large ZIPs	county charac.	N	N (ZIP Codes)
	0.407***	0.410***	0.875			89,671	14,780
	(0.156)	(0.149)					
Poverty	0.409***	0.417***	0.725	✓		88,125	14,402
	(0.162)	(0.155)					
	0.432***	0.379***	0.204		✓	90,096	15,036
	(0.161)	(0.145)					
	0.373**	0.420***	0.139			89,065	14,627
	(0.155)	(0.150)					
Low home value	0.374**	0.425***	0.120	✓		87,522	14,251
	(0.162)	(0.156)					
	0.394**	0.414***	0.725		✓	90,096	15,036
	(0.165)	(0.150)					
	0.404***	0.435***	0.289			89,825	14,864
	(0.154)	(0.145)					
Frac. black	0.410**	0.437***	0.349	✓		88,279	14,486
	(0.160)	(0.151)					
	0.345**	0.443***	0.037		✓	90,096	15,036
	(0.135)	(0.160)					
	0.408***	0.435***	0.412			89,874	14,886
	(0.153)	(0.144)					
Frac. urban	0.412***	0.439***	0.433	✓		88,328	14,508
	(0.159)	(0.149)					
	0.407***	0.437***	0.489		✓	90,096	15,036
	(0.153)	(0.145)					
	0.478**	0.427***	0.468			73,129	11,941
	(0.194)	(0.147)					
Avg. PM_{10}	0.482**	0.432***	0.490	✓		72,186	11,700
	(0.199)	(0.151)					
	0.465**	0.401***	0.410		✓	91,242	13,367
	(0.188)	(0.140)					

Notes: Each panel-column corresponds to a separate regression. Each column corresponds to smoke exposure interacted with above and below median characteristics indicated by column names. Characteristics definitions are: state-year unemployment rates (column 1), ZIP Code poverty rate estimates from ACS 2007-2011 (column 2), ZIP Code median home value estimates from ACS 2007-2011 (column 3), ZIP Code fraction of African American population estimates from ACS 2007-2011 (column 4), ZIP Code 2000-2005 average PM_{10} level (column 5), and ZIP Code fraction of urban population estimates from ACS 2007-2011 (column 6). Fire ZIP Codes include all ZIP Code-year that ever had wildfires according to the fire register data. All regressions include ZIP Code fixed effects and state×year fixed effects. Weather controls include 9 daily temperature bins, 6 annual precipitation bins, 6 daily wind direction bins, and 5 annual wind speed bins. Regressions are weighted by ZIP Code-annual number of tax exemptions. Standard errors are two-way clustered at the ZIP Code and the state×year level.

Table A.6: Heterogeneous Earnings Effects of Wildfire Smoke

Dependent variable: Log per cap. wage income (coeff. × 100)							
	smoke effect			Exclude	Interact		
	$\geq$ *median*	$<$ *median*	p value	large ZIPs	county charac.	N	N (ZIP Codes)
	-0.858***	-0.499*	0.061			176,610	28,284
	(0.260)	(0.268)					
Poverty	-1.121***	-0.612**	0.008	✓		163,101	25,738
	(0.265)	(0.266)					
	-0.711***	-0.683**	0.859		✓	177,263	28,687
	(0.240)	(0.271)					
	-0.949***	-0.553**	0.032			175,715	28,041
	(0.290)	(0.243)					
Low home value	-1.318***	-0.667***	0.000	✓		162,211	25,499
	(0.293)	(0.244)					
	-0.581***	-0.770**	0.280		✓	177,263	28,687
	(0.255)	(0.254)					
	-0.897***	0.151	0.000			176,822	28,397
	(0.241)	(0.230)					
Frac. black	-1.044***	-0.057	0.000	✓		163,313	25,851
	(0.241)	(0.241)					
	-0.811***	-0.633**	0.333		✓	177,263	28,687
	(0.238)	(0.267)					
	-0.791***	0.086	0.000			176,898	28,436
	(0.244)	(0.266)					
Frac. urban	-0.957***	-0.085	0.000	✓		163,389	25,890
	(0.244)	(0.265)					
	-0.861***	-0.189	0.000		✓	177,263	28,687
	(0.248)	(0.255)					
	-0.846***	-0.909***	0.756			87,983	13,793
	(0.314)	(0.272)					
Avg. PM_{10}	-0.945***	-0.980***	0.867	✓		85,985	13,368
	(0.317)	(0.279)					
	-0.799***	-0.765***	0.865		✓	120,607	19,130
	(0.283)	(0.261)					

Notes: Each panel-column corresponds to a separate regression. Each column corresponds to smoke exposure interacted with above and below median characteristics indicated by column names. Characteristics definitions are: state-year unemployment rates (column 1), ZIP Code poverty rate estimates from ACS 2007-2011 (column 2), ZIP Code median home value estimates from ACS 2007-2011 (column 3), ZIP Code fraction of African American population estimates from ACS 2007-2011 (column 4), ZIP Code 2000-2005 average PM_{10} level (column 5), and ZIP Code fraction of urban population estimates from ACS 2007-2011 (column 6). Fire ZIP Codes include all ZIP Code-year that ever had wildfires according to the fire register data. All regressions include ZIP Code fixed effects and state×year fixed effects. Weather controls include 9 daily temperature bins, 6 annual precipitation bins, 6 daily wind direction bins, and 5 annual wind speed bins. Regressions are weighted by ZIP Code-annual number of tax exemptions. Standard errors are two-way clustered at the ZIP Code and the state×year level.