Air Pollution and the Labor Market: Evidence from Wildfire Smoke*

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Abstract

We study how air pollution impacts the U.S. labor market by analyzing effects of drifting wildfire smoke that can affect populations far from the fires themselves. We link satellite smoke plume data with labor market outcomes to estimate that an additional day of smoke exposure reduces earnings by about 0.04 percent over two years. Employment losses can explain a third of the earnings losses. The welfare cost of the lost earnings is on par with standard valuations of the mortality effects of wildfire smoke events. The findings suggest that labor market channels warrant greater consideration in air pollution regulations.

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Ambient air pollution imposes large costs on human well-being. Among the most widely documented effects are those on health, such as increases in hospital use and premature mortality among children and the elderly (Chay and Greenstone, 2003; Jayachandran, 2009; Chen et al., 2013; Deryugina et al., 2019). Air pollution exposure can also reduce adult labor supply and productivity (Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015). However, the extent of the impact of air pollution on the labor market remains largely unknown and is often cast as limited. For example, major assessments of the economic benefits of air pollution reductions have attributed a small fraction of the benefits to labor market effects (e.g., U.S. Environmental Protection Agency, 2011; OECD, 2016). However, these assessments typically have considered only limited effects, such as lost days of work due to illness or premature mortality, potentially missing important effects arising through productivity while at work or job separations. Quantifying the broader effects of air pollution on labor market outcomes matters greatly for understanding how pollution affects human welfare and for designing efficient pollution-abatement policies.

This paper examines the medium- to long-run effects of transitory air pollution shocks on U.S. labor income and employment. A key challenge for measuring the causal effect of air pollution on nationwide labor market outcomes is finding geographically widespread fluctuations in pollution that are not themselves driven by factors that directly impact economic activity. To sidestep the joint determination of air quality and economic activity, our analysis leverages nationwide variation in U.S. air quality induced by wildfire smoke. Wildfires account for about 20 percent of the fine particulate matter emitted in the United States (U.S. Environmental Protection Agency, 2014). Wind can carry wildfire smoke for thousands of miles, generating plausibly exogenous air pollution events that are geographically dispersed, widespread, (Langmann et al., 2009), and unconnected to economic factors such as regulations. Wildfires have increased in frequency and intensity in recent years, and the burn season itself has expanded, making wildfire smoke of increasing concern as a source of pollution nationwide.

We exploit year-over-year variation in wildfire smoke exposure in a given region to estimate the medium- to long-run impacts of air pollution events on labor market outcomes. We then benchmark the welfare cost of lost earnings due to wildfire smoke by comparing them to mortality effects, which we estimate using the same research design. Our analysis relies on linking three key sources of data from 2006 to 2015: high-resolution remote sensing data from satellites that show the locations of wildfire smoke plumes in the United States,[1] air quality data from ground-level pollution monitors, and national annual labor market data.

Several features of wildfire smoke combine to create a useful natural experiment for studying the effects of air quality on labor market outcomes. Wildfire-related smoke events occur regularly throughout the United States. In 2006–2015, U.S. counties were covered by wildfire smoke for an average of 17.7 days per year on a population-weighted basis, and nearly every county experienced some exposure. Drifting wildfire smoke plumes create sharp air pollution shocks that typically last a few days and have magnitudes typical of daily variation in U.S. air quality. At the daily level, an additional day of wildfire smoke increases concentrations of fine particulate matter ($PM_{2.5}$) by an average of 2.2 $\mu g/m^3$, about one-third of the daily standard deviation.[2] At the annual level, an additional day of smoke raises a county's annual average $PM_{2.5}$ concentration by 0.021 $\mu g/m^3$, about 0.9 percent of the annual standard deviation. When we control flexibly for wind direction, we find that these estimates remain largely unaffected, indicating that wildfire smoke rather than other upwind pollution sources are responsible for the variation in air quality.

Three primary results emerge. First, we find that wildfire smoke exposure leads to statistically and economically significant losses in two-year labor income, measured in the year of exposure and the following year. Specifically, two-year labor income falls by about 0.04 percent for each additional day of smoke exposure. Effects estimated separately by year point to relatively larger effects in the year of exposure, followed by a diminished effect in the following year. By multiplying these two-year marginal effects by the average number of smoke days per year, we estimate

[1] We use wildfire smoke exposure data developed by Miller, Molitor and Zou (2017) and adapt it to fit the unit of analysis for the labor market data.

[2] The effects of air pollution from biomass burning could differ from those from car exhaust and industrial activity because biomass burns produce a different mix of pollutants, including a higher share of volatile organic compounds (VOCs). However, our mortality estimates are in line with previous effects estimated for particulate matter exposure, suggesting that wildfire smoke is comparable to other sources of pollution. We discuss this further in Section 1, and we analyze a range of pollutant responses in Section 3.

that wildfire smoke reduces earnings by about 1.5 percent of U.S. annual labor income ($93 billion in 2018 dollars) per year, on average. In a placebo test, we do not find a significant effect of smoke on income in the year prior to smoke exposure. Because we analyze annual income and allow for lagged effects, our estimates capture medium- to long-run effects of transitory air pollution shocks. In principle, the shorter-run effects that have been the focus of most prior studies of air pollution and the labor market may either overstate the longer-run effects due to intertemporal substitution in work effort or understate the longer-run effects due to lasting effects of illness or labor market disruption. Our estimates indicate that short-run estimates understate the total damage of wildfire smoke events.

Second, we estimate that an additional day of smoke exposure reduces employment by 162 employees per million residents aged 16 and older. This effect, which corresponds to a 0.026 percent decline in the employment rate, can explain nearly one-third of the total income effect of smoke exposure. We find that employment effects are larger than average among older workers, suggesting that age itself and related poor health may amplify the negative labor market effects of air pollution.[3] These results provide the first evidence linking air pollution to extensive margin responses and indicate a channel through which short-run changes in air quality may have sustained impacts on the labor market. Moreover, the estimated employment effects of smoke align qualitatively with the income effects but are estimated more precisely, reinforcing a conclusion of significant income losses due to smoke exposure.

Third, we benchmark the welfare cost of lost earnings to the cost of premature mortality due to smoke exposure. To do so, we first develop a model of health and labor supply and estimate the social welfare cost of lost earnings due to smoke exposure to be about $70 billion annually. Next, using a strategy similar to that of our earnings analysis, we estimate that each day of smoke exposure leads to 7.9 additional deaths per million residents among those aged 60 and older. Using a range of commonly used values of a statistical life, we estimate the premature mortality cost of

[3]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; Schlenker and Walker, 2016). For examples of the mortality literature, see Dockery et al. (1993) and Pope et al. (2009). See Chan and Stevens (2001) for evidence related to job search at older ages.

smoke exposure to be $19.8 billion to $76.3 billion annually. This range of mortality costs is lower than lost labor market earnings ($93 billion) and similar to or lower than the estimated $70 billion in welfare cost of these lost earnings. Our findings contrast with prior air pollution assessments that have suggested labor market costs of air pollution of less than 5 percent of the premature mortality costs in the United States (U.S. Environmental Protection Agency, 2011; OECD, 2016; World Bank, 2016). However, prior assessments of the labor market costs of air pollution have generally focused only on lost work due to illness or premature mortality, and they have relied on strong modeling assumptions in lieu of direct estimation. For example, the Environmental Protection Agency's (EPA) usual method multiplies estimates of the effects of pollution on a selection of health endpoints (such as cardiovascular or respiratory hospital admissions) by the typical number of lost work days (usually survey-collected) associated with each of those endpoints (U.S. Environmental Protection Agency, 2011). By contrast, our results are based on administrative measures of income and provide a direct comparison of mortality and labor market effects that arise from the same quasi-experimental variation in pollution exposure.

In addition to providing the first empirical evidence on the aggregate effects and relative importance of labor market channels in the evaluation of the costs of air pollution, our paper makes several other contributions to the literature. First, for pollution-abatement policy, the pollution variation we study consists primarily of variation in levels that do not exceed regulatory standards set by the EPA. Nevertheless, our findings indicate that such pollution may significantly reduce labor market earnings. Failure to consider labor market costs may therefore lead to inefficient pollution standards and regulations. Second, our findings suggest the possibility of a "double dividend" that capitalizes on the potential for reductions in air pollution to increase labor income, either through improvements in health or increased productivity. That is, reducing air pollution to align the private marginal cost of abatement with social marginal benefits can improve population health and productivity and can also generate additional income tax revenue that could be used to lower tax rates and the distortions they impose (Williams III, 2003). Moreover, our findings suggest that the magnitude of the positive income effects from other air pollution regulations is greater than previously has been recognized.

Our findings also provide evidence of how changes in health can lead to changes in employment and earnings and understanding about the conditions under which these effects are largest. The propagation of short-run labor market shocks, especially those that generate job loss, are of long-standing interest in labor and macroeconomics (Jacobson, LaLonde and Sullivan, 1993; Neal, 1995; Jarosch, 2015). Our findings that pollution shocks reduce labor income and employment add to a relatively small body of literature that documents the lasting impacts of changes in health on labor supply using quasi-experimental evidence (Coile, 2004; Stephens Jr and Toohey, 2018). Our findings suggest that workers in certain regions bear a disproportionate burden from such air pollution, including regions that have higher proportions of urban dwellers and black populations, and regions with higher home values.

Finally, our research extends the growing body of literature on the economics and social costs of natural disasters to the study of wildfire. Like the economic losses caused by other natural disasters, the damage from wildfires can be mitigated or exacerbated by policy. Our findings suggest, however, that, unlike the losses caused by most other natural disasters, the damage from wildfire arises largely from externalities, as the costs may be concentrated in locations far from the fires themselves. These social costs should be considered alongside traditional considerations of damage to property, natural resources, and the costs of firefighting, and may significantly alter optimal policy in local land use and fire management.[4] Climate change has the potential to multiply the damage from wildfires, as the National Research Council estimates that each degree Celsius increase in global temperature may lead to a quadrupling of acreage burned.[5] More broadly, these findings contribute to a growing body of literature on trans-boundary pollution with international implications, as an important share of wildfire smoke in the U.S. originates in Canada or Mexico

[4] Kochi et al. (2010) survey the literature, finding only six studies that have quantified the economic cost of wildfire smoke, and none that include economic costs manifested through the labor market.

[5] Climate change is projected to increase temperatures and reduce precipitation, leading to longer and more intense fire seasons; for example, every one-degree-Celsius increase in global temperature is projected to quadruple acreage burned by wildfires. 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. Consistent with predictions generated by these models, recent fire seasons have set records in number of fires, acreage burned, and property damage.

(Lipscomb and Mobarak, 2016; Monogan, Konisky and Woods, 2017; Yang and Chou, 2017).

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 research strategy. Section 4 reports our main results on earnings and employment responses. 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

1.1 Pollution Effects on Health and Productivity

How do transient air pollution events, such as wildfire smoke exposure, affect labor market earnings? Wildfire smoke, like other forms of air pollution, contains particulate matter that enters the lungs and can pass into the bloodstream. Smoke also carries other pollutants, such as ozone, carbon monoxide, atmospheric mercury, and a range of VOCs. A large literature in biomedical sciences, public health, and economics demonstrates negative effects of air pollution exposure on human health (e.g., Deryugina et al., 2019). A growing literature in economics has shown that exposure to these pollutants can also lead to missed work days and reduced productivity.[6] Most of these studies have focused on specific settings chosen to minimize confounding influences such as reverse causality, making it difficult to assess the incidence of air pollution on workers more generally.

While wildfire smoke is understood to operate through the same channels as other sources of air pollution, the composition of wildfire smoke may make it more harmful to human health per unit of

[6] See Hanna and Oliva (2015) and Aragón, Miranda and Oliva (2017) 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. (2016) for the productivity of agricultural workers; He, Liu and Salvo (2018) and Adhvaryu, Kala and Nyshadham (2014) for the productivity of Chinese and Indian manufacturers, respectively; Chang et al. (2019) for the productivity of indoor call center workers; Lichter, Pestel and Sommer (2017) and Archsmith, Heyes and Saberian (2018) for the performance of soccer players and baseball umpires, respectively; and 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 and tourism.

measured particulate matter.[7] Miller, Molitor and Zou (2017) use national-scale variation in daily smoke exposure to document a link between smoke exposure and adult mortality and morbidity. Using conventional figures for the value of a statistical life-year, they find that the mortality cost of wildfire smoke is significantly higher than the hospital-related morbidity cost as captured by health care spending. Case studies of wildfire smoke anomalies have also found suggestive evidence that the mortality cost of wildfire smoke exceeds the morbidity cost (e.g. Kochi et al., 2012, 2016). Wildfire smoke can also cause significant damage to infant health (Jayachandran, 2009; McCoy and Zhao, 2016).

In addition to directly affecting human health, air pollution may also cause individuals to take costly avoidance or defensive actions (Chay and Greenstone, 2005; Moretti and Neidell, 2011; Graff Zivin and Neidell, 2013; Deschênes, Greenstone and Shapiro, 2017). For wildfire smoke in particular, survey research has documented various behavioral responses, such as spending more time indoors, running air conditioners for longer times, and missing work (Jones et al., 2015). For example, Richardson, Champ and Loomis (2012) examine a large wildfire in California in 2009 and estimate that the economic costs of health effects are comprised primarily of avoidance, defensive actions, and disutility, with only about 10 percent of costs due to illness.

Effects of air pollution on labor markets may arise from a combination of health effects and avoidance actions occurring during and shortly after air pollution events. More significant losses may occur if short-run pollution effects catalyze longer-run labor market responses. Yet little is known about the long-run effects of transient air pollution shocks in adulthood on either health or labor markets. Theoretically, short-run health effects of air pollution may result in lasting earnings losses over a longer time through either health channels or interactions with the labor market. Biomedical mechanisms exist through which short-run exposure may affect medium- and long-run health. Most directly, once particulate matter enters the body, it may take weeks or months for it to clear. In addition, transient exposure may result in adverse health events, such as heart attacks

[7] Research on the differences in the composition of smoke from biomass burning and car exhaust finds 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., 2009, 2015; Bates et al., 2015). Wildfires have also been found to produce higher levels of gaseous and particulate pollutants than prescribed burns (Liu et al., 2017).

or the onset of asthma, reducing health capital and leaving exposed individuals more vulnerable to future health shocks. For example, exposure to adverse economic and environmental conditions in early childhood can lower educational attainment and earnings later in life (Case, Lubotsky and Paxson, 2002; Sanders, 2012; Isen, Rossin-Slater and Walker, 2017).

Temporary labor market disruptions can also have lasting impacts on earnings and welfare, as shown in numerous studies of displaced workers and labor market entrants (Jacobson, LaLonde and Sullivan, 1993; Kahn, 2010; Oreopoulos et al., 2012; Borgschulte and Martorell, 2017). Many workers in the United States have weak job protections when they or family members fall ill.[8] Wages may respond to more serious illnesses due to lasting changes in workers' productivity or employment. We know of no evidence on the effects of such 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., 2018).

1.2 Conceptual Model of Health and Labor Supply

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 days, $s(c)$. Pollution concentration may represent a vector of harmful components in wildfire smoke. An agent maximizes utility that

[8] 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).

depends on consumption, X, leisure, l, sick days, s, and exposure, c:

$$\mathbf{max}_{X,l} U(X,l,s,c)$$

$$\text{s.t. } Y + wh \geq X$$

$$l = T - s - h$$

Consumption will equal non-labor income, Y, and earnings, wh. Wages respond to pollution, $w = w(c)$, due to a combination of responses through three channels: changes in the returns to work arising from a decay in human capital after an illness, the incidence of labor demand changes on workers , and 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:

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

The first bracketed term in equation (2) captures the direct effects of pollution 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, $(1+\eta_s)$, scales the endogenous labor supply response to changes in the wage; as wages fall 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 on wages and endogenous labor supply response.

The primary focus of the paper is on estimating $\frac{dE(c)}{dc}$, 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, we return in Section 5 to equation (2) to guide our analysis of the welfare effects of the lost earnings.

2 Data

Our analysis relies on a novel, nationwide linkage of data on wildfire smoke exposure, air pollution, weather conditions, labor market outcomes, and mortality. These data derive from a wide variety of sources, including satellite imagery, environmental monitors, federal income statistics, nationally representative surveys, and vital statistics records. This section describes the construction of the database and the definitions of our key variables used in the analysis.

2.1 Wildfire Data

A key innovation of our analysis is to link labor market outcomes to annual counts of wildfire smoke exposure nationwide at the county level. The daily smoke exposure data were originally developed by Miller, Molitor and Zou (2017) using wildfire smoke analysis produced by the National Oceanic and Atmospheric Administration's Hazard Mapping System (HMS). The HMS uses observations from the Geostationary Operational Environmental Satellite, which produces imagery at a 1-km resolution for visual bands and a 2-km resolution for infrared bands, to identify fire and smoke emissions over the contiguous United States (Ruminski et al., 2006). Smoke analysts process the satellite data to draw georeferenced polygons that represent the spatial extent of wildfire smoke plumes detected each day. We use the HMS smoke plume data from 2006 to 2015 to construct smoke exposure at the county level for each day in this period. Our primary measure of smoke exposure is an indicator for a county being fully covered by a smoke plume on a day.

We complement the satellite smoke observations with wildfire records from the National Fire and Aviation Management group of the U.S. Forest Service, which combines records from seven major fire and wildland management agencies: the Bureau of Indian Affairs, the Bureau of Land

Management, the Bureau of Reclamation, the California Department of Forestry and Fire Protection, the National Park Service Fire and Aviation Management, the U.S. Fish & Wildlife Service, and the U.S. Forest Service. We use the wildfire location data to identify areas that may have been directly affected by the burning of fires.

2.2 Pollution Data

We obtain ambient air pollution data from the EPA's Air Quality System. We use daily ground monitor readings for EPA "criteria pollutants," including fine particulate matter ($PM_{2.5}$), coarse particulate matter (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 increase during wildfire events and because the EPA recognizes them as the most important pollutants that affect human health.

To measure air pollution for a county, we take the weighted average of all valid readings for each pollutant from monitors that fall within 20 miles of a county's centroid, where the weights are the inverse of the distance between the monitor and the county centroid. This pollution measure is missing for counties in which the nearest pollution monitor with a valid reading is outside the 20-mile radius.[9] Because monitors for some pollutants are more prevalent than monitors for others, data availability differs by pollutant. For example, 1,642 counties in our sample have O_3 data, but only 691 counties have NO_2 data. The 1,300 counties for which we can measure $PM_{2.5}$ represent the area of residence for about 70 percent of the U.S. population. Most of the area is urban.

2.3 Weather Data

To flexibly control for weather patterns in our analysis, we obtain daily measures of temperature, precipitation, and wind patterns. Temperature and precipitation data are from the Global Historical

[9] Areas and days with missing data are mostly due to the U.S. EPA's goal of cost-effectively monitoring urban air quality. In areas with monitoring systems, data can be missing on some days due to intermittent monitoring schedules and, occasionally, equipment failure. The 20-mile inverse distance weighting is intended to maximize the usage of available data and to interpolate pollution readings within a reasonable distance range. We do not otherwise interpolate or fill in missing pollution readings.

Climatology Network of the National Climatic Data Center. The data provide daily, station-level information on minimum temperature, maximum temperature, and total precipitation. To construct weather conditions at the county level, we average daily weather readings from stations that fall within 20 miles of each county's centroid, weighting readings by the inverse of the distance between the station and the county centroid.

We obtain wind speed and wind direction data from the North American Regional Reanalysis (NARR) of the National Centers for Environmental Information. NARR divides the United States into 32km$\times$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 Labor Market Data

We use county-annual labor market outcomes data derived from various data sources, all of which are national in scope. Our primary measures of earnings and employment come from the U.S. Census Bureau Quarterly Workforce Indicators (QWI), which cover all workers except for members of the armed forces, self-employed individuals, proprietors, and railroad employees. The QWI provide information by age group, allowing us to measure employment effects separately for younger and older workers. We supplement the QWI data with measures of retirement and disability insurance benefits data from the Regional Economic Information System (REIS) of the Bureau of Economic Analysis (BEA). Data on labor force participation are from the Local Area Unemployment Statistics (LAUS) program of the U.S. Bureau of Labor Statistics.

In supplemental analyses, we consider robustness to using earnings measures from three alternative sources: the U.S. Census Bureau's County Business Patterns (CBP), the REIS, and the Internal Revenue Service's (IRS) Individual Income Tax Statistics. Each of these data sources provide measures of county-level annual earnings, but they differ slightly in population coverage.[10]

2.5 Mortality Data

Mortality outcomes are measured in micro-data provided by the National Vital Statistics System. The underlying data are taken from death certificates which contain age of death. We use the restricted data files containing month of death and covering all counties in the United States to measuring monthly mortality at the county level. The data are available for the entire sample period (2006–2015).

3 Research Strategy

Identifying the causal effects of air pollution on labor markets is challenging for three primary reasons. First, observational correlations between air pollution and economic activity may be due in part to the causal effects of the economic activity on air pollution. 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 that 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 a relationship between pollution and labor markets has generally focused on studies of specific industries or regions. These specific settings may not produce nationally representative effects and may not generate sufficient variation to study relatively rare but significant outcomes, such as retirement or mortality.

[10]CBP are based on the U.S. Census Bureau's Business Register, which excludes data on self-employed individuals, employees of private households, railroad employees, agricultural production employees, and most government employees. IRS data, which are based on stratified probability samples of individual income tax returns as reported on Forms 1040, 1040A, and 1040EZ, include only workers who file tax returns by the end of the calendar year that follows the year of tax liability (See <https://www.irs.gov/pub/irs-soi/sampling.pdf>). REIS uses administrative records from various federal and state government social insurance programs, such as the State unemployment insurance programs, Medicaid and Medicare programs, Social Security, Federal veterans' programs, and tax codes from the IRS.

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 permit a research design that addresses the identification challenges described above.

First, wildfire smoke plumes are a natural source of air pollution and travel hundreds or even thousands of miles downwind, allowing us to identify the effects of smoke exposure separately from direct damages caused by wildfire burns.[11] Figure 1 provides summary statistics for the annual frequency and spatial distribution of smoke events in our sample. Counties are fully covered by smoke plumes for 17.7 days per year on average (on a population-weighted basis). Smoke exposure tends to be highest in the upper Midwest but significantly varies from year to year.

Second, smoke shocks increase air pollution concentrations by magnitudes large enough to likely generate significant health and behavioral responses. Panel A of Table 1 shows that wildfire smoke increases daily concentrations of each pollutant we examine, with the largest relative effects on particulate matter and ozone. An average smoky day increases $PM_{2.5}$ by 2.2 $\mu g/m^3$ on the day of exposure, about one-third of a standard deviation in the distribution of daily particulate matter. Panel B of Table 1 reports the effect of a smoke day on annual pollution. We estimate that increasing smoke exposure by one day increases annual $PM_{2.5}$ by 0.021 $\mu g/m^3$. This is equivalent to increasing $PM_{2.5}$ by 7.67 $\mu g/m^3$, or more than three times the single-day exposure level. This implies 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 changes in air quality that are often not visible to the human eye. This underscores that our estimates are not driven by a small number of days during which people are exposed to intense smoke. Extreme wildfire smoke events can 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

[11] Appendix Figure A.1 depicts an example of smoke exposure across much of North America during the Fort McMurray fires in northern Canada. Fires in the U.S. Southeast also appear in the figure.

in our data lie within the normally experienced levels of air quality, helping to allay this concern. To characterize the typical footprint of a smoke exposure day on air quality on surrounding the event, we conducted an event study using PM2.5 as the outcome variable, and "time since the smoke plume was recorded" as the event time (Figure 2). Smoke days are associated with elevated levels of fine particulate matter for four days, with an average increase of just over 2 $\mu g/m^3$ on the day of exposure relative to the daily mean of 10.2 $\mu g/m^3$ (see Table 1). To put this into context, the EPA's annual standard for $PM_{2.5}$ is 15 $\mu g/m^3$, while the daily $PM_{2.5}$ standard is 35 $\mu g/m^3$, far above most exposure levels. Thus, although wildfire smoke is a unique source of pollution, it seems plausible that behavioral responses to smoke—especially far from the fires themselves—will be similar to those caused by other fluctuations in air quality.

Finally, we note that the wind patterns that carry wildfire smoke to a region may also bring in pollution from other sources. Even if this were the case, our research design nevertheless captures the causal labor market effects of pollution shocks. In this case, however, part of the effect we find could then stem from upwind pollution sources other than wildfires. To make the distinction between potential pollution sources, we directly examine the extent to which wind patterns can explain the wildfire smoke effects we document. Motivated by the research design in Deryugina et al. (2019), we examine daily first stage estimates of the pollution effect of wildfire smoke plume coverage with and without state- or county-specific current and lagged wind direction (60-arc degree) bins (Appendix Figure A.2 reports the results.) The smoke effect estimates change little across specifications. Our annual labor market effect estimates also change little when we control for annual wind patterns (see Appendix Table A.3 for further detail). These results provide evidence supporting our interpretation that the pollution effects we observe are driven by wildfire smoke plumes, rather than by generically dirty wind patterns.

3.2 Identifying the Effect of Smoke Exposure on Labor Market Outcomes

Our research strategy exploits year-over-year variation in the number of wildfire smoke days in a county, and it also controls flexibly for potential time-varying correlates of smoke (such as weather patterns) to identify the labor market effects of smoke exposure. We aggregate the daily smoke exposure data to the annual level to construct our focal independent variable, $SmokeDays_{ct}$, which equals the number of days in year t in which county c was exposed to wildfire smoke. We then estimate the following regression equation:

$$Y_{ct} = \beta \cdot SmokeDays_{ct} + SmokeDays_{c,t+1} + \alpha_c + \alpha_{st} + X_{ct}\gamma + \varepsilon_{ct}. \tag{3}$$

The estimating equation includes county fixed effects (α_c) to isolate year-over-year variation in smoke exposure at the county level. State-by-year fixed effects (α_{st}) account for annual smoke shocks that may coincide with regional labor market trends, such as those driven by the Great Recession. We also control flexibly for weather patterns that may directly affect labor market outcomes and may also be correlated with smoke exposure. The time-varying weather controls X_{ct} include annual counts of the number of days exposed to different temperature ranges (10-degree Fahrenheit bins of daily average temperature), rain (quadratic annual precipitation), wind indicators (60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed), and an indicator variable for whether any wildfires occurred in the county that year. We weight regressions by county population in each year. To adjust for both within-county and state-year autocorrelation, we cluster standard errors at both the county and state-by-year levels.

For our baseline analysis, the dependent variable, Y_{ct}, is a measure of labor market outcomes in county c over a two-year event window beginning with the index year t. We focus on two classes of labor market outcomes: earnings and employment. We measure two-year earnings by summing earnings in a county in years t and $t+1$ and then taking the log. We measure employment, including labor market participation outcomes, by averaging the participation rates (the number of participants per million population) in years t and $t+1$. The primary coefficient of interest, β, reflects the effect of an additional day of wildfire smoke in the exposed county on the outcome variable. We control for smoke exposure in year $t+1$ so that β captures the net effect of smoke this year on labor market outcome over the two-year time window.[12] Because the outcomes are defined

[12] In the raw data, each additional day of smoke exposure in a county in a year is associated with 0.65 additional

over a two-year event window, the estimated effects account for both short-term displacement effects and lagged effects of smoke.

As an alternative approach, we also estimate a dynamic version of equation (3) that relies on annual (one-year) outcomes and adds lagged smoke exposure for years $t-1$ and $t-2$. An advantage of the dynamic specification is that coefficients on lagged smoke exposure describe whether and for how long the effects of smoke persist after exposure. Additionally, coefficients on lead terms provide a "placebo" check of our approach to identification because outcomes should not be influenced by quasi-random future smoke shocks. A disadvantage of the dynamic specification relative to the more parsimonious two-year specification is that we lose two years of data by adding the two years of smoke lags. In robustness checks, we therefore also report results that exclude leads and lags of smoke.

4 Results

4.1 Annual Earnings

4.1.1 Baseline results

Table 2 presents results from estimating equation (3) for earnings, employment, and retirement benefits. Panel A reports our two-year estimates, which reflect the effect of smoke exposure in year t on outcomes in years t and $t+1$. In Panel B, we report a dynamic specification that includes the effect of the next year's exposure to smoke (i.e., in year $t+1$) on this year's income—a placebo check—and the lagged effects of previous years' exposure to smoke (i.e., in years $t-1$ and $t-2$). A disadvantage of the dynamic specification is that we must drop two years of observations to accommodate the additional lags. When examining magnitudes in the dynamic specification, it is important to note that the average smoke season centers on mid-July, meaning that about half the days in a year follow a smoke event, on average. We report raw estimates in the tables, but

days of smoke exposure in the following year. Including county fixed effects, state-by-year fixed effects, and weather controls reduces this association to 0.07 additional days of smoke. Thus, conditional on these controls, there is little year-over-year serial correlation in wildfire smoke exposure.

annual-level effects on year t outcomes should be roughly doubled to derive post-exposure effects that can be compared with effects in the following years.

As shown in column 1 of Panel A, we find that each day of wildfire smoke exposure in a county reduces average annual wage and salary earnings as reported in the QWI by 0.041 percent in the year of exposure and the following year. Estimated dynamic effects in Panel B suggest that smoke exposure leads to earnings losses of 0.042 (p-value = 0.087) in the year of exposure and 0.030 (p-value = 0.130) the following year.[13] Given that smoke exposure most typically occurs midyear, these point estimates suggest that the post-exposure effect in year t is about three times as large in the effect in year $t+1$. The very small point estimate on the effect of smoke in year $t-2$ suggests that the earnings effects of smoke are concentrated within two years of exposure, which supports the appropriateness of using a two-year, post-event window for our baseline specification. Moreover, the estimate on future smoke in year $t+1$ is negligible, consistent with quasi-random smoke exposure events.

The point estimates imply large effects of wildfire smoke on national labor income if one assumes that the effects of the marginal smoke day estimated here reflect the average effect of smoke days. In 2010, approximately 160 million U.S. workers earned a total of $6.4 trillion (in 2018 dollars).[14] To estimate the total earnings losses from a typical year of smoke exposure, we multiply two-year earnings (about $12.8 trillion) by both the estimated reduction of 0.041 percent in two-year earnings per day of smoke exposure and by the average number of smoke days per year (17.7) in our sample. This gives total earnings losses of $92.9 billion (about 1.5 percent of annual earnings) per year of smoke exposure. It is important to acknowledge that the income loss estimates have relatively wide confidence intervals; however, their alignment with the dynamic pattern of employment effects, discussed below, provide additional evidence on the plausibility of significant income losses due to smoke exposure.

Another way to assess the magnitude of our point estimates, and to compare them to prior

[13]The average of the year t and year $t-1$ effects of the annual effect specification is -0.036 (SE=0.021, p=0.095).

[14]Total wage and salary compensation was $6.4 trillion in 2010, as reported by the BEA. We use the Consumer Price Index to convert to 2018 dollars.

studies, is to scale them by the increases in particulate matter caused by the wildfire smoke. While particulate matter is viewed as especially harmful pollutants to human health, we provide this exercise with great caution: wildfire smoke carries many types of pollutants, so attributing the entire effect to particulate matter may overstate the effect of that one pollutant. Dividing the two-year earnings effect of a typical year of smoke (about 1.5 percent of annual earnings) by the effect on annual $PM_{2.5}$ concentrations ($0.21 \times 17.7 = 0.37$ $\mu g/m^3$) implies that a 1 $\mu g/m^3$ (approximately 10 percent) increase in annual $PM_{2.5}$ concentrations generates earnings losses amounting to about 4 percent of annual earnings. By comparison, Aragón, Miranda and Oliva (2017) found that a 10 percent increase in $PM_{2.5}$ reduced hours of work by as much as 2 percent in the week following exposure. Hanna and Oliva (2015) found that a 10 percent decrease in SO_2 concentrations increased hours worked by 1.5 percent, while Chang et al. (2019) found that a 10 percent increase in $PM_{2.5}$ reduced productivity per hour by 0.6 percent. Our long-run estimates are 2 to 7 times larger than these short-run estimates, indicating that our estimates are large but consistent with existing evidence. Finally, we note that average concentrations of $PM_{2.5}$ declined steadily from about 13 $\mu g/m^3$ in 1999 to about 8 $\mu g/m^3$ in 2015.[15] This decline of about 5 $\mu g/m^3$ would imply a total earnings increase of about 20 percent of annual earnings if, in fact, all the harms of smoke were caused by the particulate matter component of smoke alone.

4.1.2 Robustness checks

We perform several additional analyses and robustness checks, with results reported in the Appendix. First, we re-estimate our main specification, equation (3), for earnings reported in three other datasets: the CBP, the BEA, and the IRS Statistics of Income. The results are similar to those based on the QWI earnings measure used for our baseline analysis.

Next, we test whether smoke exposure affects migration into and out of a county. We measure net migration flows (i.e., population size) using the total number of tax exemptions claimed in an area using IRS data. We also directly measure in- and out-migration using IRS county-to-county

[15] Source: <https://www.epa.gov/air-trends/particulate-matter-pm25-trends>.

flows. The results, reported in Appendix Table A.2, indicate that population migration does not respond to smoke exposure to an economically or statistically significant degree. The lack of a population migration response to smoke exposure suggests that our main effects are not artifacts of regional changes in population composition.

We also examine how our results respond to the inclusion of increasingly flexible wind controls. As discussed in Section 3.1, if wind patterns that carry wildfire smoke also bring in pollution from other sources, part of the effects we estimate may be driven by the other upwind pollution sources. Appendix Figure A.2 shows that controlling flexibly for wind direction has little effect on our first-stage estimates of the air pollution effects of smoke events. Similarly, Appendix Table A.3 reports that annual labor market effect estimates change very little when we control for Census Division- or state-specific annual wind patterns (this specification lacks the degrees of freedom for county-specific wind controls). These findings support interpreting our main estimates as the incremental effects of smoke plume shocks.

We examine alternative clustering choices for the calculation of the standard errors. Appendix Table A.3, Panel D, shows that the choice to cluster at the county and state-by-year level has almost no effect on inference in our setting.

As a final robustness check, we estimate the impact of year t's smoke exposure on year t's labor market outcome, ignoring dynamic impacts of smoke (i.e., excluding leads and lags of smoke exposure). The estimated effects of smoke from this specification, reported in Panel E of Appendix Table A.3, are similar to the year t coefficients in the dynamic specification reported in Table 2.

4.2 Extensive Margin and Retirement Behavior

An important but previously mostly unanswered question is whether transitory air pollution episodes leave lasting impacts on labor markets. Our model in Section 1 highlights two channels through which such lasting impacts could occur. First, air pollution may cause health events, such as asthma episodes or heart attacks, which lead to chronic health conditions. These chronic conditions may reduce workers' productivity and labor supply or may even cause them to leave the labor force altogether. Second, diminished health, whether temporary or chronic, may affect labor market opportunities. A large literature in labor economics documents the lasting effects of job loss, suggesting that particularly large losses may occur with changes in the extensive margin labor force attachment. Because the health of older workers may be more sensitive to pollution shocks, we hypothesize that smoke effects should be strongest among older workers, potentially generating losses associated with labor market transitions and retirements.

We use equation (3) to test for smoke effects on employment in the following ways. First, we estimate the effect of smoke on labor force participation (LFP) responses as measured by BLS LAUS data. As reported in Column 2 of Table 2, each day of wildfire smoke reduces LFP in the county by 119 per million individuals aged 16 and over.[16] Second, we estimate the effect of smoke on employment, as measured by the QWI. Column 3 reports that for all workers ages 16 and older, each day of smoke exposure reduces employment by 162 employees per million residents, a 0.026 percent decline relative to the sample average employment rate of 62.5 percent. As with the main earnings results, the dynamic specifications closely resemble the primary specifications. There is no sign of effects of next year's smoke (a placebo check), and there is a diminished estimated effect of the previous year's smoke.

We next turn to responses among older individuals, a group whose health is likely to be more vulnerable to smoke exposure. Appendix Figure A.3 reports estimated employment effects separately for 10-year age groups from 25-54 and for age group 65 and older. The largest responses (both in terms of level and percentage changes) are for individuals age 55 to 64, and 65 and older. Column 4 of Table 2 summarizes the employment effects at older ages. Employment of workers ages 55 and older declines by 121 employees per million residents per day of smoke exposure—a 0.033 percent reduction in employment among this group. Reduction in employment of older workers may partly reflect retirements. To examine this, column 5 reports estimated effects of smoke exposure on retirement and disability benefit income (including Social Security income), as reported by the BEA. Point estimates are positive, as would occur if smoke exposure increased

[16] We divide county employment by the county's population aged 16+, and then we multiply the number by 1,000,000 for sake of readability.

claiming of retirement and disability benefit claiming, but the estimates are not statistically different from zero.

The dynamic pattern of employment effects aligns with that of the income effects but is estimated more precisely, providing additional support for a conclusion of significant income losses due to smoke exposure. Moreover, part of the effects of smoke exposure on income can be explained by the extensive margin employment effects. If those who leave the labor force earn average incomes, and if the reduction in labor supply lasts one year, the employment effects of a day of smoke exposure would reduce annual income by 0.026 percent for one year. By comparison, each day of smoke exposure reduces annual income by 0.041 percent for two years (Table 1). Thus, the employment reductions due to smoke can account for nearly one-third (0.026/0.082) of the total income effect of smoke exposure. This calculation illustrates the potential for relatively small but recurring shocks to employment to have large effects on total earnings.

4.3 Heterogeneity by County Characteristics and Industry

We explore how pollution effects vary with county characteristics to shed light on the conditions under which labor markets are the most sensitive to pollution shocks. To do so, we create indicators for whether a county is above- or below-median with respect to each of five characteristics: fraction that is urban, fraction in poverty, median home value, fraction that is black, and the 10-year (2006-2015) average $PM_{2.5}$ concentration. For each characteristic, we estimate heterogeneity in the two-year earnings effects of smoke exposure using an augmented version of equation 3 that replaces the smoke exposure variable with interactions between smoke exposure and indicators for whether the county is above- or below-median for the given characteristic.

Table 3 reports the results of this heterogeneity analysis, along with p-values that correspond to testing equality of the effects for above- versus below-median counties. We estimate that smoke exposure causes larger earnings declines in regions that are above-median in the fraction that is urban, the fraction in poverty, median home value, and the fraction that is black relative to counties that are below-median in each of these characteristics (all differential effects are statistically significant, except for the fraction in poverty). We estimate that the earnings effects of smoke exposure are similar in regions that above- and below-median in average $PM_{2.5}$ concentration.

To explore heterogeneity in earnings effects of smoke exposure by industry, we estimated equation 3 separately for each 2-digit NAICS industry code. Results are reported in Appendix Figure A.4. For many industries, estimated effects are imprecise. We do find a relatively precise zero in agriculture; this finding contrasts with prior work finding that pollution reduces short-run productivity in some agricultural settings (e.g., Graff Zivin and Neidell, 2012). Our results could differ from these prior settings both because the agriculture sector in our data is more broadly defined (it includes sectors such as crop and animal production, logging, and fishing) and because we estimate long-run effects that are net of short-run intertemporal substitution.

5 Welfare

5.1 Air Pollution and Welfare

In this section, we estimate the social welfare costs associated with lost earnings due to wildfire smoke exposure, and we compare this to the welfare cost of premature deaths caused by smoke exposure. Lost earnings themselves do not necessarily equate to reductions in social welfare for two primary reasons. First, lost earnings coming from reductions in labor supply inflate deadweight losses associated with pre-existing tax distortions in labor markets. Second, some portion of the lost earnings may be explained by increased leisure or by the replacement of market work with home production, such as if workers stay home on high-pollution days or are forced into early retirement by smoke-related illness.

5.1.1 The Double Dividend through Increased Labor Income

Studies in public and environmental economics consider how air pollution regulation interacts with the tax-distorted labor market. While taxes on pollution may or may not generate any benefits in the labor market (Goulder, 1995; Fullerton and Metcalf, 2001), pollution regulations that improve labor incomes through health and productivity channels can produce a "double dividend" (Schwartz and Repetto, 2000; Williams III, 2002, 2003). This source of welfare gains arises because increases in labor supply alleviate pre-existing tax distortions associated with payroll and income taxes.

Calibrating the changes in welfare through this channel is straightforward in partial equilibrium. On the margin, increases in labor supply will reduce the deadweight loss by an amount that equals the change in labor multiplied by the average marginal tax rate for affected individuals. While we do not directly measure this tax rate in our sample, we can take a moderate value of 25% to calculate that welfare increases by one-quarter of the total loss, or $23 billion of the $93 billion.

5.1.2 Individual Welfare

For individual welfare, we can perform a simple calculation building on the models in Section 1 and in Dobkin et al. (2018) and from estimates reported in Table 2. To focus attention on the labor market costs, we separate workers' losses that occur through consumption and leisure (X and l) from direct losses arising from changes in health and amenities (s and c). We label utility from consumption and leisure as $U^{LM}(X,l)$. Normalizing by the marginal utility of consumption gives the labor market component of welfare, W^{LM}. In the next subsection, we return to the issue of costs arising from illness. We also simplify the model by dropping avoidance behavior, and focusing on long-run effects, motivated by the persistent losses we find in the earnings analysis. Individual welfare losses arise from endogenous labor supply responses, reductions in the wage, and reductions in the time endowment due to illness. Social welfare losses include these changes in addition to changes in deadweight loss, i.e., the double dividend channel.

Considering a small change in pollution concentration, c, the loss in money-metric utility to the worker 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 can then take the ratio of the above individual welfare loss to the lost earnings in order to calibrate the appropriate scaling of the earnings losses.

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 to individuals. We focus on the case in which all responses arise from changes in the wage, as in Dobkin et al. (2018), but also consider changes in the time endowment to provide an informative upper bound. Specifically, individual welfare losses as a share of earnings losses lie between the wage response, $\frac{1}{1+\eta_{h,w}}$, 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. (2018)), to estimate that two-thirds of the earnings loss reflect true costs to the worker.

5.1.3 Social Welfare

Social welfare combines both individual welfare losses and changes in deadweight loss from taxation. In the case where earnings losses arise from responses to the wage, social welfare losses are the sum of individual losses and the deadweight loss of the labor supply response due to taxation, which can be calculated by multiplying the marginal tax rate by the difference between earnings responses and the individual welfare loss.[17] Assuming a marginal tax rate of 25% and $\eta_{h,w} = 0.5$ implies a social welfare effect of 75% (two-thirds from labor supply plus one-twelfth from deadweight loss) of lost earnings.

Applying the above model to the estimates reported in Table 2, we find that the welfare losses working through labor market responses are \$70 billion in 2018 dollars. The lasting damage to labor market opportunities 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

[17] Intuitively, lost earnings that arise from labor supply response are replaced by leisure in the individual's utility. However, this leisure is subsidized by the government at the marginal tax rate, leading to deadweight loss.

shock), or worker transitions to lower-paid jobs induced by illness or labor-demand effects. Losses may approach an upper bound of \$93 billion, if responses occur entirely through perfectly inelastic responses, as when workers are constrained from working by illness. Alternatively, at a lower bound where all lost income arises from perfectly elastic labor-supply responses, social welfare falls by 25% of lost earnings, or \$23 billion. We regard this scenario as unrealistic; it is informative primarily because it generates important welfare responses entirely through the double dividend channel, and applies under the most pessimistic model of individual behavior. 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.

5.2 Comparison with Mortality Costs

To evaluate the importance of incorporating labor market effects into estimates of air pollution costs, we benchmark the welfare costs of lost earnings to those of premature deaths due to smoke exposure. We estimate the mortality effect of smoke exposure at the monthly level, the temporal level of our mortality data, using a regression specification that closely mirrors equation (3) from our earnings analysis. The outcome, M_{cmy}, is measured as deaths per million in county c, month of the year m, and year y. We regress this outcome on the number of days $SmokeDays_{cmy}$ in which the county was exposed to wildfire smoke that month:

$$M_{cmy} = \beta \cdot SmokeDays_{cmy} + \alpha_{cm} + \alpha_{sy} + X_{cmy}\gamma + \varepsilon_{cmy}. \tag{4}$$

The primary coefficient of interest is β, which describes the effect of an additional day of smoke on mortality in the month of exposure. To account for delayed mortality effects as well as possible short-run mortality displacement (harvesting), we also estimate specifications in which mortality is measured over 3-, 6-, and 12-month windows beginning with the month of exposure. We include the same weather controls, X_{cmy}, as in equation (3) and add fixed effects for county by month to control for seasonality in mortality. The 3-, 6-, and 12-month specifications further control for number of smoke days in the corresponding look-ahead window. Standard errors are two-way clustered at the county and state by year levels.

Table 4 reports the results of the mortality analysis. Across all ages (column 1), we estimate positive but statistically insignificant increases of 0.14 and 0.25 deaths per million within the first month and 3 months of exposure, respectively. As the post-exposure window increases to 6 months, the estimated effect increases to a statistically significant all-age mortality increase of 1.17 deaths per million. Further extending the post-exposure window to a year produces a smaller and statistically insignificant all-age mortality estimate.

Columns 2 and 3 of Table 4 report mortality effects of smoke exposure estimated separately by age group. We estimate small and statistically insignificant effects among individuals under the age of 60. Among individuals aged 60 and older, we estimate that each day of smoke increases mortality by 1.37, 3.23, 7.90 and 2.19 deaths per million within 1, 3, 6, and 12 months of smoke exposure, respectively. The findings are statistically significant for all time frames, except for the 12-month period effect. The pattern of an increasing mortality effect up to 6-months after exposure points to some delay in mortality effects and also indicates that the effect is not driven by very short-term (less than 6 months) mortality displacement. At the same time, the estimated effect does not continue to grow but instead becomes smaller after 12 months. Because the 6-month point estimate is slightly larger than the upper limit of the 12-month estimate's 95 percent confidence interval, we interpret the 6-month estimate as an upper bound on the annual lives lost per day of smoke exposure.

To calculate the welfare cost of smoke mortality, we scale the age group-specific mortality effects to annual lives lost and multiply by a value of statistical life. To calculate annual lives lost, we multiply the 6-month mortality effect of smoke among the population aged 60 and older (7.9 deaths per million per day of smoke) by the size of this population in millions (59.0, per the 2012 U.S. Census) and the average number of smoke days per year (17.7). This implies approximately 8,250 lives lost per year due to smoke. We consider two alternative values for lost lives. First, the EPA uses a value of $9.25 million ($2018) per statistical life regardless of population characteristics such as age, implying annual mortality costs of $76.3 billion. Second, we use a value of $2.4 million per statistical life that accounts for lower-than-average life expectancy among adults ages 60 and older. We calculate this by multiplying $150,000 per year of life lost (Cutler and Richardson, 1999) (in $2018) by the average remaining life expectancy of 16.1 among this population.[18] This second value implies annual mortality costs of $19.8 billion.

A key feature of the analysis is that we use the same source of variation in both the earnings and mortality analyses, facilitating a direct comparison of labor market and mortality costs. We find that mortality costs ($19.8 billion to 76.3 billion) are lower than the lost labor market earnings ($93 billion) and similar to or lower than our preferred estimate of $70 billion in welfare cost of these lost earnings. Even our lower bound of $23 billion in welfare costs due to lost earnings slightly exceeds the $19 billion mortality cost estimate that accounts for life years lost. These comparisons imply that labor market responses comprise a large share of the welfare costs of wildfire smoke, and such costs should be taken into account when evaluating the overall costs of air pollution.

6 Discussion and Conclusion

Wildfires severely damage the areas they burn, destroying homes and property and threatening human lives in their path. Wildfires also emit smoke plumes that contain harmful pollutants and can drift for hundreds or thousands of miles, regularly affecting populations far from the fires themselves. We analyze annual variation in wildfire smoke exposure across the United States and find that increases in smoke exposure cause significant decreases in earnings and employment outcomes. In addition, we find that the welfare cost of these lost earnings is similar to or larger than the cost of increased mortality due to the same wildfire smoke exposure. Although wildfire smoke has a different chemical composition than industrial pollution or vehicle exhaust, the large labor market costs of wildfire-emitted pollutants—which comprise a significant share of all U.S. particulate matter emissions—suggest that other pollutants that negatively affect health may have

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

similarly large labor market costs.

Our results provide the first quasi-experimental evidence of the effect of air pollution events on labor markets at a national scale. These results have broad implications for environmental policy. Many agencies that engage in environmental policymaking, such as the Organisation for Economic Co-operation and Development, the World Bank, and the U.S. EPA, have traditionally treated pollution damages arising from lost labor market hours and earnings as considerably smaller than the mortality cost of air pollution. Our findings indicate that environmental policies that ignore or downplay the labor market effects of air pollution fail to take into account significant costs, and such policies may thus be inefficient. Our results also suggest that employment-reducing effects of environmental regulation to improve air quality could be partially offset by earnings and employment gains to workers, in addition to the reduced health costs that are more broadly part of the wider policy calculus.

Our findings also have direct implications for wildfire policy and management. A primary implication of our results is that wildfire smoke creates large externalities. That is, decisions about land use and fire management in one location can have profound effects on those living in other regions downwind. These widespread effects call for greater coordination of fire policy efforts, including a focus on preventing the start and spread of wildfires. Policies should consider factors that go beyond narrower goals of defending land and property exposed to fires in a given region, such as the amount of smoke produced by the fire and whether the smoke plumes that may reach urban centers. The use of prescribed fires to remove fuel and limit the scope for larger future burns should likely expand, although such fires should be set only after taking into account wind patterns to avoid population exposure. Finally, estimates of the marginal cost of wildfire suppression and prevention, which we hope will receive more attention in future research, should consider the costs of both reducing the acreage burned and reducing the population exposed to smoke. While wildfires and smoke cannot and should not be completely eliminated, planning and optimal policy can and should better mitigate damages from these events by assessing the full scope of their effects.

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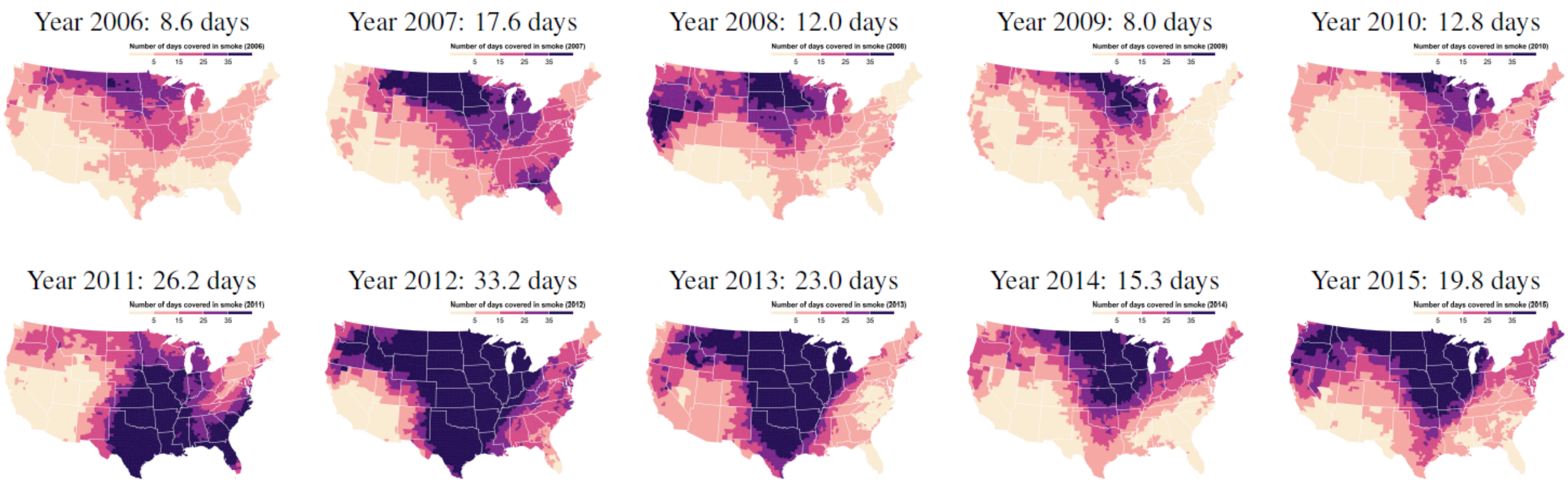
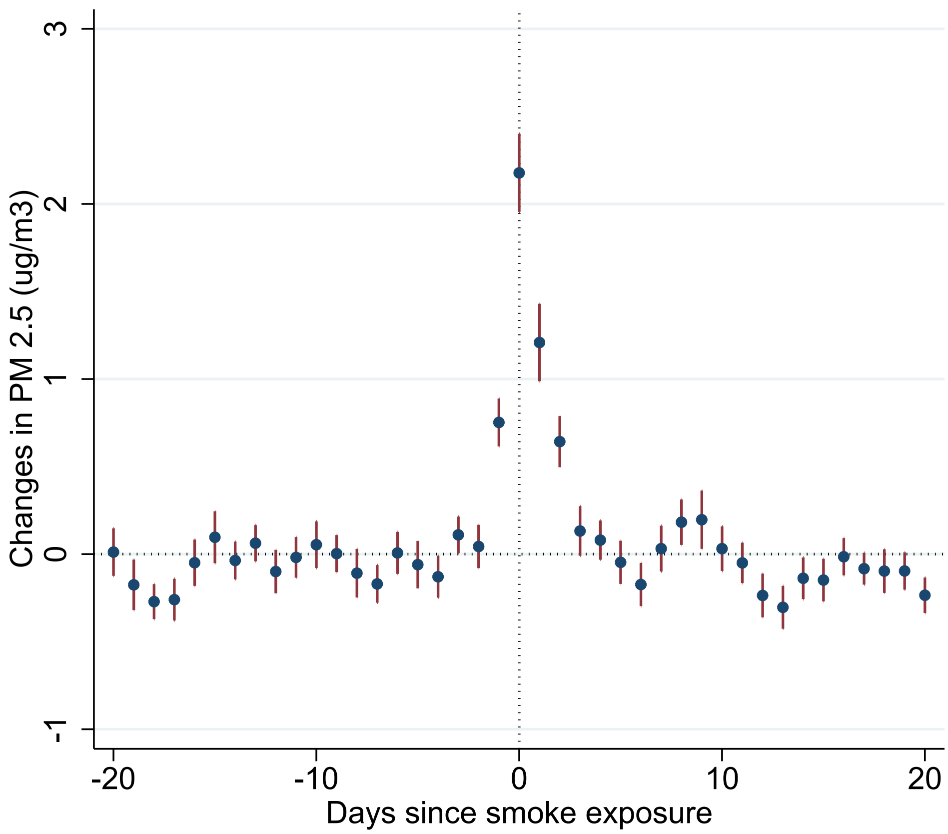
Figure 1: County Annual Wildfire Smoke Exposure 2006–2015



Notes: This figure plots county-level average annual days of smoke exposure for the lower 48 states for each year from 2006 to 2015. Average population-weighted exposure during this period was 17.7 days per year. Grayscale shading indicates quintiles of smoke exposure: 0–5 days (lightest shading), 6–15 days, 16–25 days, 26–35 days, or more than 35 days (darkest shading).

Figure 2: Air Pollution Effects of Wildfire Smoke: Daily-Level Event Study



Notes: This figure shows coefficients from a regression of daily $PM_{2.5}$ on indicators of daily smoke exposure up to 20 days before and after the day of observation. In addition to the 41 smoke indicators, the regression controls for county-by-week-of-year fixed effects, state-by-year fixed effects, day-of-week fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic daily precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Daily observations for years in which a county experienced a wildfire are excluded. Standard errors are clustered at both the county and the state-by-year levels.

Table 1: Air Pollution Effects of Wildfire Smoke

	(1)	(2)	(3)	(4)	(5)	(6)
	$PM_{2.5}$ (ug/m3)	PM_{10} (ug/m3)	O_3 (ppb)	CO (ppb)	NO_2 (ppm)	SO_2 (ppm)
Panel A. Daily effect						
1(Smoke)	2.173***	3.743***	3.162***	11.190***	0.530***	0.157***
	(0.118)	(0.179)	(0.147)	(1.063)	(0.068)	(0.022)
Panel B. Annual effect						
Smoke days	0.021**	0.046	0.022***	-0.088	-0.015	0.004
	(0.009)	(0.034)	(0.007)	(0.407)	(0.010)	(0.005)
Mean dep. var. (panel A)	10.19	22.03	28.09	373.33	12.15	1.68
SD dep. var. (panel A)	6.02	13.26	10.59	172.16	7.57	2.53
Mean dep. var. (panel B)	10.38	21.11	27.39	360.17	11.89	1.94
SD dep. var. (panel B)	2.35	7.53	4.28	113.91	5.22	1.45
Number of observations (panel A)	2,338,609	1,347,701	3,640,761	1,594,882	1,714,565	2,566,112
Number of observations (panel B)	14,774	10,395	16,976	6,058	6,865	9,310

Notes: The table reports estimated effects of a day of wildfire smoke on pollution that day (panel A) and an additional day of wildfire smoke exposure on annual pollution (panel B). Each panel-column corresponds to a separate regression using county-daily/annual observations and county population weights. Daily-level regressions include county-by-week-of-year fixed effects, state-by-year fixed effects, day-of-week fixed effects, 3 leads and 3 lags of smoke day indicators, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic daily precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily wind speed. Annual-level regressions include county fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Daily-level regressions exclude observations for years in which a county experienced a wildfire. Standard errors are clustered at both the county and the state-by-year levels.

Table 2: Labor Market Effects of Wildfire Smoke

	(1)	(2)	(3)	(4)	(5)
	Income (log)	LFP (ages 16+)	Employment (ages 16+)	Employment (ages 55+)	Retirement & disability income (log)
Panel A. Two-Year Effect					
Smoke days (year t)	-0.041**	-119.3*	-161.7**	-121.3***	0.021
	(0.020)	(70.4)	(71.2)	(42.0)	(0.015)
Panel B. Annual Effect					
Smoke days (year $t+1$)	0.004	-5.7	18.4	-44.4	0.006
	(0.018)	(90.5)	(82.7)	(46.5)	(0.014)
Smoke days (year t)	-0.042*	-129.1*	-160.5***	-100.3**	0.008
	(0.024)	(73.3)	(56.4)	(40.6)	(0.014)
Smoke days (year $t-1$)	-0.030	-104.4	-21.2	-58.5	0.005
	(0.020)	(71.6)	(55.9)	(36.3)	(0.014)
Smoke days (year $t-2$)	-0.005	24.8	-4.7	-77.9	0.015
	(0.017)	(60.9)	(67.3)	(47.4)	(0.016)
Data source	QWI	BLS	QWI	QWI	BEA
Mean per capita outcome (panel A)	45,456	633,521	624,878	364,714	5,471.3
Mean per capita outcome (panel B)	22,083	628,539	610,314	358,561	2,727.3
Number of observations (panel A)	27,557	27,602	27,557	27,557	27,304
Number of observations (panel B)	21,440	21,466	21,440	21,440	21,229

Notes: The table reports estimated effects of an additional day of wildfire smoke exposure on labor market outcomes. Units of measurement are log per capita scaled up by 100 (income, retirement & disability income) and count per million population (LFP, employment ages 16+, employment ages 55+). Panel A reports regressions using two-year (current year and next year) outcome as the dependent variables. Panel B reports regressions using current-year outcome as the dependent variables. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. "Mean per capita outcome" reports the mean of per capita income (column 1) and per capita benefits (column 5) in 2018 dollars. Each column corresponds to a separate regression using county-year observations and relevant county population weights. All regressions include county fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Regressions in panel A (two-year effects) further controls for a lead term in annual smoke days. Standard errors are clustered at both the county and the state-by-year levels.

Table 3: Heterogeneous Wage Income Effects of Wildfire Smoke

	(1)	(2)	(3)	(4)	(5)
County characteristics:	%urban	%poverty	Home value	%black	Avg. $PM_{2.5}$
Smoke days $\times$ 1($<$median)	-0.001	-0.032	-0.016	-0.033	-0.042*
	(0.020)	(0.021)	(0.019)	(0.021)	(0.022)
Smoke days $\times$ 1($\geq$median)	-0.047**	-0.050**	-0.045**	-0.059***	-0.039*
	(0.019)	(0.019)	(0.020)	(0.020)	(0.023)
p-value	0.000	0.130	0.004	0.009	0.824
Number of observations	27,557	27,557	27,557	27,557	15,467

Notes: The table reports heterogeneous effects of an additional day of wildfire smoke exposure on two-year (current year and next year) income. Unit of measurement is log per capita scaled up by 100. Each column corresponds to a separate regression using county-year observations and relevant county population weights. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. Interaction terms are county-level above- and below-median indicators for fraction of urban population (column 1), fraction of population living under 100% of the Federal Poverty Line (column 2), median home value (column 3), share of African American population (column 4), average $PM_{2.5}$ during the study period (column 5). p-value corresponds to the null that there is no differential effect of smoke across above- and below-median groups. All regressions include county fixed effects, state-by-year fixed effects, a lead term in annual smoke days, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Regressions in panel B (two-year effects) further controls for a lead term in annual smoke days. Standard errors are clustered at both the county and the state-by-year levels.

Table 4: Mortality Effects of Wildfire Smoke

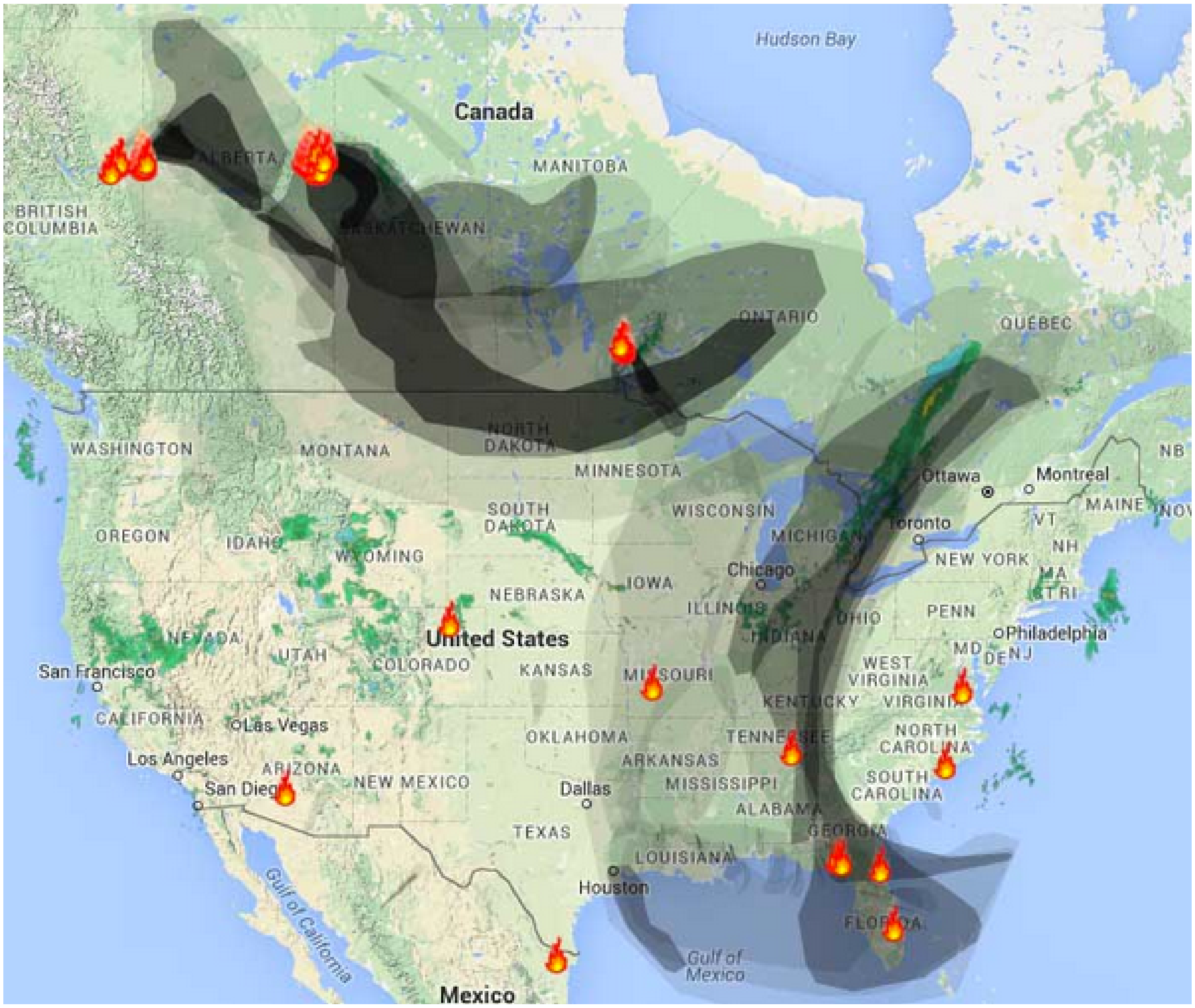
	(1)	(2)	(3)
	All ages	Ages 60−	Ages 60+
Panel A. 1-Month Effect			
Smoke days	0.140	0.060	1.372**
	(0.113)	(0.040)	(0.561)
Panel B. 3-Month Effect			
Smoke days	0.247	0.060	3.234***
	(0.234)	(0.078)	(1.070)
Panel C. 6-Month Effect			
Smoke days	1.174***	0.034	7.903***
	(0.436)	(0.119)	(1.926)
Panel D. 12-Month Effect			
Smoke days	0.382	-0.263	2.186
	(0.542)	(0.198)	(2.288)
Life years lost per death	44.5	50.4	16.1
Mean mortality rate (1-month)	678.2	168.9	2,869.2
Mean mortality rate (3-month)	2,033.7	506.5	8,618.8
Mean mortality rate (6-month)	4,068.1	1,012.7	17,289.9
Mean mortality rate (12-month)	8,153.5	2,024.4	34,885.3
Number of observations (panel A)	362,295	362,295	362,295
Number of observations (panel B)	350,565	350,565	350,565
Number of observations (panel C)	336,950	336,950	336,950
Number of observations (panel D)	314,069	314,069	314,069

Notes: The table reports estimated effects of an additional day of wildfire smoke exposure on monthly mortality rate. k-month mortality is the number of deaths in the next k months (including the current month) divided by relevant population. Unit of measurement is number of deaths per million population. Each panel-column corresponds to a separate regression using county-monthly observations and relevant county population weights. The focal independent variables capture the number of days in a month on which a county was exposed to wildfire smoke. All regressions include county-by-month-of-year fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic monthly precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Regressions in panels B, C, and D control additionally for number of smoke days in the corresponding look-ahead windows. Standard errors are clustered at both the county and the state-by-year levels.

A Online Appendix

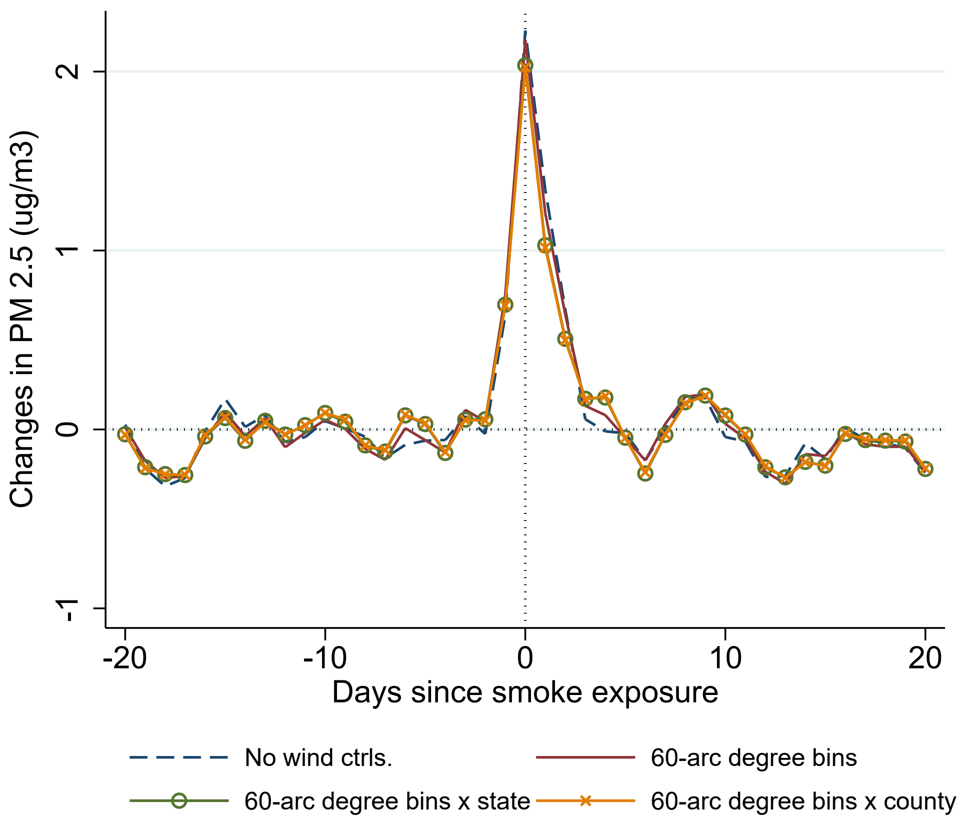
Online Appendix Figures and Tables

Figure A.1: Fire and Smoke on May 7, 2016



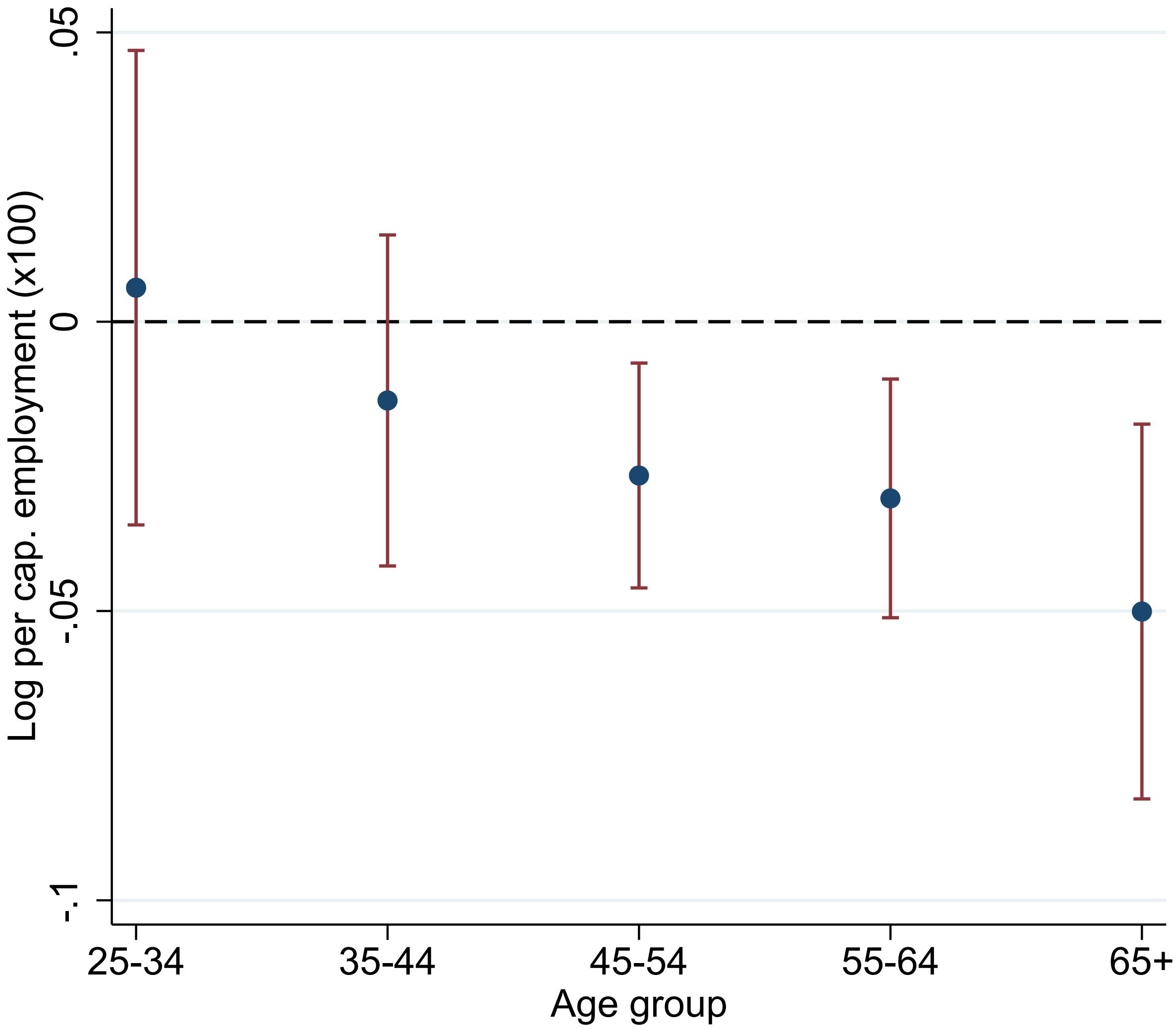
Notes: This map depicts smoke patterns on May 7, 2016 at 9:20 AM. The Fort McMurray fires in Northern Canada can be seen north of Alberta. This large wildfire produces a smoke plume that reaches the upper Midwest. Wildfires in the U.S. Southeast produce plumes reaching Canada. Source: WeatherUnderground.com via WildfireToday.com.

Figure A.2: Air Pollution Effects of Wildfire Smoke: Robustness to Flexible Wind Controls



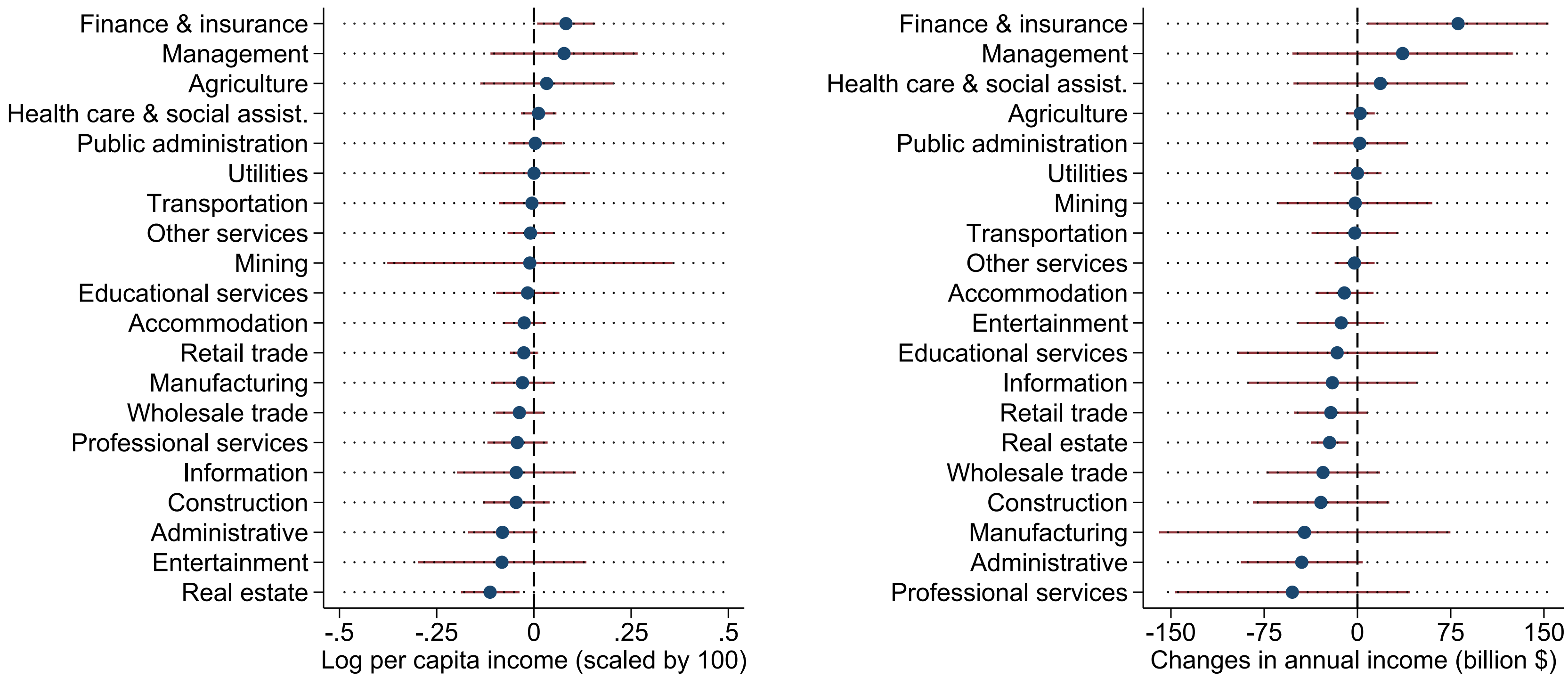
Notes: This figure shows coefficients from a regression of daily $PM_{2.5}$ on indicators of daily smoke exposure up to 20 days before and after the day of observation. Three specifications show varying degrees of controls of wind direction: no controls, 60-arc degree bins of daily wind direction, 60-arc degree bins of daily wind direction fully interacted with state dummies, and 60-arc degree bins of daily wind direction fully interacted with county dummies. In addition to the 41 smoke indicators, the regression controls for county-by-week-of-year fixed effects, state-by-year fixed effects, day-of-week fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic daily precipitation, and quintile bins of daily average wind speed. Daily observations for years in which a county experienced a wildfire are excluded. Standard errors are clustered at both the county and the state-by-year levels.

Figure A.3: Employment Effects of Wildfire Smoke: Age Profile



Notes: The figure reports estimated effects (current plus lagged effect) of an additional day of wildfire smoke exposure on two-year employment per capita separately for different age groups. The dependent variable is the log of per capita employment rate as measured by QWI, scaled by 100. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. Coefficients reflect percentage changes in per capita employment per day of smoke in the relevant age group. All regressions include county fixed effects, state-by-year fixed effects, a lead term in annual smoke days, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic daily precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Standard errors are clustered at both the county and the state-by-year levels.

Figure A.4: Wage Income Effects of Wildfire Smoke: Industry Profile



Notes: The figure reports estimated two-year (current year and next year) effects of an additional day of wildfire smoke exposure on log per capita (left) and economy-wide total (right) annual income separately for 2-digit NAICS industries. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. All regressions include county fixed effects, state-by-year fixed effects, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Standard errors are clustered at both the county and the state-by-year levels.

Table A.1: Wage Income Effect of Wildfire Smoke: Alternative Data Sources

	(1)	(2)	(3)	(4)
	Income	Income	Income	Income
Smoke days	-0.041**	-0.040**	-0.031*	-0.038**
	(0.020)	(0.018)	(0.018)	(0.018)
Data source	QWI	CBP	BEA	IRS
Mean per capita income (2-year)	45,456	38,028	49,297	48,508
Number of observations	27,557	27,346	27,304	27,631

The table reports estimated effects of an additional day of wildfire smoke exposure on two-year (current year and next year) income measured using different data sources. Unit of measurement is log per capita scaled up by 100. Each column corresponds to a separate regression using county-year observations and relevant county population weights. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. "Mean per capita income" reports the mean of per capita income in 2018 dollars. All regressions include county fixed effects, state-by-year fixed effects, a lead term in annul smoke days, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Unless noted otherwise, standard errors are clustered at both the county and the state-by-year levels.

Table A.2: Migration Effects of Wildfire Smoke

	(1) In-migration (log)	(2) Out-migrantion (log)	(3) Tax exemptions (log)
Smoke days	-0.000	-0.011	0.012
	(0.016)	(0.013)	(0.015)
Data source	IRS	IRS	IRS
Number of observations	27,604	27,605	27,615

Notes: The table reports estimated effects of an additional day of wildfire smoke exposure on two-year (current year and next year) migration outcomes. Units of measurement are log per capita scaled up by 100 (in-migration and out-migration) and log scaled up by 100 (tax exemptions). Each column corresponds to a separate regression using county-year observations and relevant county population weights. The focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. All regressions include county fixed effects, state-by-year fixed effects, a lead term in annul smoke days, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Unless noted otherwise, standard errors are clustered at both the county and the state-by-year levels.

Table A.3: Labor Market Effects of Wildfire Smoke: Robustness

	(1)	(2)	(3)	(4)	(5)
	Income (log)	LFP (ages 16+)	Employment (ages 16+)	Employment (ages 55+)	Retire.& DI benefits (log)
Panel A. Smoke measure = sum of smoked fraction					
Smoke days	-0.030	-48.3	-143.8**	-111.1***	0.027**
	(0.019)	(71.0)	(64.3)	(35.2)	(0.013)
Panel B. Flexible wind controls: Census Division-specific wind directions					
Smoke days	-0.037**	-85.7	-163.0**	-108.4**	0.019
	(0.018)	(77.7)	(74.5)	(44.0)	(0.015)
Panel C. Flexible wind controls: State-specific wind directions					
Smoke days	-0.036*	-67.5	-156.1*	-102.9**	0.018
	(0.020)	(89.5)	(87.5)	(50.2)	(0.016)
Panel D. Alternative SE clustering					
Smoke days	-0.041	-119.3	-161.7	-121.3	0.021
SE: county & division×year	(0.020)**	(76.9)*	(71.0)***	(43.7)***	(0.015)
SE: county	(0.019)**	(55.5)***	(66.3)***	(30.3)***	(0.011)*
SE: state	(0.019)**	(83.6)	(69.8)***	(47.2)***	(0.017)
Panel E. One-year effect					
Smoke days	-0.036*	-114.8	-160.7**	-126.0***	0.022
	(0.021)	(85.7)	(77.7)	(48.4)	(0.017)
Data source:	QWI	BLS	QWI	QWI	BEA
Number of observations (panels A-D)	27,557	27,602	27,557	27,557	27,304
Number of observations (panels E)	30,615	30,660	30,615	30,615	30,329

Notes: The table reports estimated effects of an additional day of wildfire smoke exposure on two-year (current year and next year) labor market outcomes (panels A-D) and one-year labor market outcomes (panel E). Units of measurement are log per capita scaled up by 100 (income, retirement DI benefits) and count per million population (LFP, employment ages 16+, employment ages 55+). Panel A reports regressions where smoke days is measured by the sum of daily coverage "fraction" (the share of land a county is covered in smoke). Panel B controls additional for 60-arc degree bins of daily prevailing wind direction fully interacted state dummies. Panel C reports robustness to alternative standard error clustering. Each column-panel corresponds to a separate regression using county-year observations and relevant county population weights. Except for panel A, the focal independent variables capture the number of days in a year on which a county was exposed to wildfire smoke. All regressions include county fixed effects, state-by-year fixed effects, a lead term in annul smoke days, and weather controls for 10-degree Fahrenheit bins of daily temperature, quadratic annual precipitation, 60-arc degree bins of daily prevailing wind direction, and quintile bins of daily average wind speed. Unless noted otherwise, standard errors are clustered at both the county and the state-by-year levels.