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 the effects of drifting wildfire smoke. We link satellite-based smoke plume data with labor market outcomes to estimate that an additional day of smoke exposure reduces quarterly earnings by about 0.1 percent. Extensive margin responses, including employment reductions and labor force exits, explain 13 percent of the overall earnings losses. The implied welfare costs from lost earnings due to air pollution exposure is on par with standard valuations of the mortality burden. The findings highlight the importance of labor market channels in air pollution policy responses.

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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; Anderson, 2020). Air pollution exposure can also reduce 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 aspects, such as lost days of work due to illness or premature mortality, potentially missing important effects arising through job separations or productivity while at work. Quantifying the broader effects of air pollution on labor market outcomes matters greatly both for understanding how pollution affects human welfare and for designing optimal air quality policies.

This paper examines the medium-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 variation in 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, and unconnected to economic factors such as regulations (Langmann et al., 2009). Wildfires have increased in frequency and intensity in recent years, making them an increasing concern as a source of pollution nationwide.

In our analysis, we exploit variation in wildfire smoke exposure at the county level to estimate the impacts of transient air pollution events on labor market outcomes. Our analysis relies on linking three primary data sources from 2007 to 2019: 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 labor market data for all counties in the continental United States. To facilitate comparison of our estimates to those from prior studies, we report both reduced-form effects of wildfire smoke and instrumental variables (IV) models that use smoke exposure as an instrument for local concentrations of fine particulate matter ($PM_{2.5}$). We then benchmark the welfare costs of lost earnings due to pollution by comparing them to mortality costs derived from established estimates in the literature.

Several features of wildfire smoke combine to create a useful natural experiment for studying the effects of air quality on labor market outcomes. Wildfire smoke events occur regularly throughout the United States. During our study period, U.S. counties were fully covered by wildfire smoke for an average of 20.2 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 have magnitudes typical of daily variation in U.S. air quality. At the daily level, an additional day of wildfire smoke increases concentrations of ground-level fine particulate matter ($PM_{2.5}$) by an average of 2.2 $\mu g/m^3$, about one-third of the daily standard deviation. The relationship between smoke exposure and $PM_{2.5}$ can also be detected at the quarterly level, which is the time frequency at which we conduct labor market analysis. We show that an additional day of smoke raises a county's quarterly average $PM_{2.5}$ concentration by about 0.06 $\mu g/m^3$. When we control flexibly for wind direction, we find that these estimates remain largely unaffected, indicating that wildfire smoke rather than other pollution sources upwind are responsible for the variation in air quality.

Our study has three primary results. First, we find that wildfire smoke exposure leads to statistically and economically significant losses in labor income, employment, and labor force participation (LFP). We estimate that each day of smoke reduces quarterly per capita earnings by $5.2, or about 0.1 percent. Multiplying this effect by the average number of smoke days each year, we calculate that wildfire smoke reduces earnings by nearly 2 percent of U.S. annual labor income ($125 billion in 2018 dollars) per year on average between 2007 and 2019. We find that the ef-

[1] We use wildfire smoke exposure data developed by Miller, Molitor and Zou (2021) and adapt it to fit the unit of analysis for the labor market data.

fect of smoke is larger than average among older workers, suggesting that age and related poor health may amplify the negative labor market effects of air pollution.[2] On the extensive margin, we show that an additional day of smoke exposure reduces employment by 80 employees per million residents aged 16 and older; this can explain 13 percent of the total earnings effect of smoke exposure, assuming that those who lost employment earn average incomes. We further document a reduction in LFP of 39 per million people, consistent with some employment losses resulting in labor force exits. These results provide novel evidence linking air pollution to extensive margin labor responses and indicate a channel through which short-run changes in air quality may have sustained impacts on the labor market.

Second, we leverage plausibly exogenous variation in wildfire smoke exposure to provide one of the first national estimates of the causal effect of ambient air pollution exposure on labor market outcomes. Our baseline estimates imply that a 1 $\mu g/m^3$ increase in quarterly $PM_{2.5}$ concentrations reduces per capita earnings in the quarter by \$103, reduces employment by 1,750 workers per million residents aged 16 and older, and reduces LFP by 791 individuals per million people. All three estimates are an order of magnitude larger than their ordinary least squares (OLS) counterparts, which reinforces the importance of a research design that addresses measurement error and endogeneity.[3] Our estimates capture medium-run effects of transitory air pollution shocks, which differ from the shorter-run effects that have been the focus of most prior studies of air pollution and the labor market, such as those examining effects on piece-rate workers in agricultural, manufacturing, and service settings. While our findings are based on national data covering income from nearly every industry, our baseline estimate of the effect of air pollution on earnings is typical of effects

[2]Medical and public health studies find that vulnerability to respiratory and circulatory illness rises with age, suggesting that 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.

[3]One caveat that we discuss further in Section 3.3 involves the interpretation of the IV estimate as the causal effect of an *independent* increase in $PM_{2.5}$, as air pollutants tend to correlate with each other, an issue that applies generally to studies of the impact of air pollution. In our study context, we document that wildfire smoke indeed generates an omnibus increase of multiple pollutants, though most predominantly for ground-level $PM_{2.5}$ and, to a smaller degree, for PM_{10} and O_3. We interpret the IV broadly as the effect of bad air quality as proxied by $PM_{2.5}$. While our IV design does not pin down the effect of individual pollutants, in Appendix Table A.3, we report a multivariate OLS analysis which provides supportive evidence that $PM_{2.5}$ appears to be the strongest predictor for earnings losses among criteria pollutants recognized by the U.S. Environmental Protection Agency.

found in prior studies, suggesting that air pollution affects labor markets broadly, and not just in narrowly defined settings.

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 stylized model of health and labor supply, which allows us to gauge social welfare losses based on our IV estimate of the earnings effect of $PM_{2.5}$. We provide a back-of-the-envelope estimate that the annual social welfare costs of lost earnings are about \$92 billion per 1 $\mu g/m^3$ annual increase in $PM_{2.5}$. Next, we quantify the mortality costs of $PM_{2.5}$ using established estimates from Deryugina et al. (2019), who leverage quasi-random variation in wind patterns to identify causal effects of $PM_{2.5}$ on elderly mortality at the daily frequency for the entire United States.[4] Using a range of commonly used values of a statistical life, we calculate the premature mortality costs of $PM_{2.5}$ from wildfire smoke to be between \$8.1 billion and \$31.3 billion annually. These estimates are lower than our estimates of smoke-related losses in earnings (\$123 billion) and the welfare costs (\$92 billion) of these losses. Our findings contrast sharply with prior air pollution assessments that put labor market costs of air pollution at less than 5 percent of the premature mortality costs in the United States (U.S. Environmental Protection Agency, 2011; OECD, 2016; World Bank, 2016). These assessments 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 usual method employed by the Environmental Protection Agency (EPA) multiplies estimates of the effects of pollution on a selection of health endpoints (such as cardiovascular or respiratory hospitalizations) by the typical number of lost work days (usually taken from surveys) associated with each 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 quasi-experimental variation in pollution exposure.

[4]While our preferred calculation is based on existing estimates from independent studies, we also provide a complementary analysis by leveraging the smoke quasi-experiment again and directly estimating the mortality effects of smoke (and the resulting pollution increases) using mortality data available at the monthly frequency. Though less powered than the daily analysis of Deryugina et al. (2019), our estimates are broadly in line with those of the literature, and produce similar conclusions on the mortality costs of $PM_{2.5}$ exposure.

In addition to providing novel 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. The first concerns pollution abatement policy. Though the pollution variation we study primarily occurs below regulatory standards set by the EPA, our findings nevertheless indicate that such pollution significantly reduces 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 supply, thereby both raising labor income and alleviating the tax distortion associated with labor income taxes (Williams III, 2003). Moreover, our findings suggest that the magnitude of the positive income effects from other air pollution regulations may be 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 offer an improved understanding of the conditions under which these effects are largest. The propagation of short-run labor market shocks, especially those that generate job losses, are of long-standing interest in the labor and macroeconomics literatures (Jacobson, LaLonde and Sullivan, 1993; Neal, 1995; Jarosch, 2021). Our findings that pollution shocks reduce labor income and employment add to a small but growing literature that documents the lasting impacts of changes in health on labor supply using quasi-experimental evidence (Coile, 2004; Stephens Jr and Toohey, 2018). We also find evidence that workers bear a disproportionate burden from such air pollution in certain regions, including those that have a higher Black population share.

Finally, our research adds to a growing body of literature on the economic and social costs of natural disasters and on how policies can be designed to mitigate disaster impacts. While damages from many natural disasters tend to be localized, our findings show that drifting smoke from wildfires creates an externality that can inflict significant losses in locations far from the fires themselves. These social costs should be considered alongside traditional considerations of wildfire damages to property and natural resources and the costs of firefighting when designing policies for local land use and fire management.[5] In addition, our findings contribute to a growing body of literature on trans-boundary pollution with international implications, as an important share of wildfire smoke in the United States originates in Canada or Mexico (Lipscomb and Mobarak, 2016; Monogan, Konisky and Woods, 2017; Yang and Chou, 2017). Climate model predictions that wildfire events will increase in frequency and severity underscore the importance of advancing our understanding of the impacts of these events.[6]

1 Background and Conceptual Framework

1.1 Pollution Effects on Health and Productivity

How does exposure to transient air pollution events such as wildfire smoke affect labor market earnings? Wildfire smoke 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 volatile organic compounds (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). 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 or less harmful to human health per unit of measured particulate matter.[7] The health effects of wildfire smoke exposure have been linked to increases in adult mortality (Miller, Molitor and Zou, 2021), increases in infant mortality (Jayachandran, 2009), elevated risk of low birth weight (McCoy and Zhao, 2016), and reductions in lung capacity (Pakhtigian, 2022).

[5] Kochi et al. (2010) survey this 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.

[6] 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.

[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 than in 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).

Air pollution can also affect non-health outcomes (see Aguilar-Gomez et al., 2022, for a review). For example, air pollution may 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; Barwick et al., 2019). For wildfire smoke in particular, survey research has documented various behavioral responses, such as spending more time indoors, running air conditioners longer, and missing work (Jones et al., 2015). Burke et al. (2021) documents a host of awareness and behavior changes, including health-protective behaviors, mobility, and sentiment, in response to increasing wildfire pollution. Prior studies have found that air pollution exposure can also lead to missed work days and reduced productivity.[8] Most of these studies have focused on specific settings chosen to minimize simultaneity issues such as reverse causality, making it difficult to assess the incidence of air pollution on workers more generally.

While various studies have examined the short-run effects of transient air pollution shocks in adulthood, relatively little is known about longer-run effects, which could be more significant if short-run pollution effects catalyze longer-run health and labor market responses. 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 or the onset of asthma, reducing health capital and leaving exposed individuals more vulnerable to future health shocks. Looking at very long-run effects of health on income, 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).

[8] See Hanna and Oliva (2015) and Aragón, Miranda and Oliva (2017) for air pollution's effects on hours worked; Hausman, Ostro and Wise (1984), Hansen and Selte (2000) and Holub, Hospido and Wagner (2020) 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 (2022) 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 performance on tests. 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.

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.[9] 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, though previous researchers have relied on such effects to motivate models of linkages between health and labor markets. For example, lower wages may be an important 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 stylized 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. Pollution concentration may represent a vector of harmful components in wildfire smoke. An agent maximizes utility that 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

[9]The Family Medical Leave Act covered 59 percent of workers in 2012, and it 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).

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, $s \equiv s(c)$, are directly subtracted. Hours of work, $h \equiv h(w(c), c)$, respond to wages and direct avoidance of high pollution.

The resulting earnings function is $E(c) = w(c) \cdot h(w(c), s(c), c)$. Taking derivatives and rearranging yields a decomposition of the reduced-form effect:

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

The first bracketed term in equation (1) 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 the 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, in Section 5 we revisit equation (1) to guide our analysis of the welfare effects of lost earnings.

2 Data

2.1 Wildfire Smoke Data

A key innovation of our analysis is to link labor market outcomes to wildfire smoke exposure at the county level. The daily smoke exposure data were originally developed by Miller, Molitor and Zou (2021) 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. Plumes are typically drawn twice per day, once shortly before sunrise and once shortly after sunset. We use the HMS smoke plume data from 2007 to 2019 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. In Section 4.4, we describe robustness checks in which we calculate smoke exposure based on the fraction of a county's area that is covered by smoke plumes.

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). The EPA recognizes these pollutants as the most detrimental to 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; 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. Because there are more monitors for some pollutants than for others, data availability differs by pollutant. For example, 1,837 counties in our sample have O_3 data, but only 863 counties have NO_2 data. The 1,686 counties for which we can measure $PM_{2.5}$ represent the area of residence for over 85 percent of the U.S. population.

2.3 Weather Data

In sensitivity checks, we flexibly control for weather patterns including temperature, precipitation, and wind patterns. We acquire temperature and precipitation data from the Global Historical 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 data on wind speed and wind direction 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 measure quarterly labor market outcomes at the county level using data from two main sources with national coverage. Our primary measures of earnings and employment come from the U.S. Census Bureau Quarterly Workforce Indicators (QWI) dataset, which covers all workers except for those who are members of the armed forces, self-employed, proprietors, and railroad employees. The QWI provides information by age group and by two-digit industry codes, using the North American Industry Classification System (NAICS), allowing us to measure effects separately for younger and older workers and for workers in different industry sectors. Data on LFP are from the Local Area Unemployment Statistics (LAUS) program of the U.S. Bureau of Labor Statistics. LAUS provides county-level labor force counts for each month, which we aggregate to quarterly averages to match the temporal frequency of the QWI earnings and employment measures.

3 Research Strategy

Attempts to identify the causal effects of air pollution on labor markets face at least three primary challenges. First, observational correlations between air pollution and economic activity may partly reflect the causal effects of economic activity on air pollution (reverse causality) or some other factor that affects both economic activity and air pollution. These challenges can potentially be overcome using an instrumental variables strategy, but a valid instrument in this setting must be uncorrelated with unobserved determinants of labor market outcomes. For example, regulatory policies that reduce air pollution may impose direct effects on the regulated markets and are thus unlikely to be valid instruments. 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 studies of how pollution affects labor markets have generally focused on specific industries or regions. This approach is generally unable to capture effects on labor market exits or shifts in labor market activity from one industry to another, and it also raises questions about whether findings are nationally representative.

3.1 Wildfire Smoke and Air Quality

To address these challenges, we use variation in wildfire smoke exposure to identify the causal effects of transient air pollution shocks on labor markets. 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.[10] Figure 1 maps the number of days each U.S. county was fully covered in smoke in each year of the 2007-2019 sample period. Over this period, counties experience an average of 20.2 smoke days per year, on a population-weighted basis. Smoke exposure tends to be highest in states in the West North Central Census Division but varies substantially from year to year.

We first characterize how smoke events map to ground-level air quality at the daily level. To

[10] 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.

do so, we conduct an event study by regressing the concentration of ambient fine particulate matter ($PM_{2.5}$) in a county c and on day d on a series of indicators for smoke exposure on each day within 20 days of the index day, using the following regression.

$$[PM_{2.5}]_{cd} = \sum_{\tau=-20}^{20} \beta_\tau \cdot SmokeDay_{c,d+\tau} + \alpha_{c \times day\text{-}of\text{-}year} + \alpha_{state \times year} + \varepsilon_{cd}. \tag{2}$$

Fixed effects for county by day of the year isolate year-over-year variation in smoke exposure at the county level, absorbing county-specific seasonality. Fixed effects for state by year further account for annual trends in smoke exposure, which may vary by state. The β_τ coefficients trace out the typical footprint of ground-level air quality surrounding a smoke day.

The daily-level event study helps illustrate the nature of a typical smoke shock in our data. In part because air pollution may linger even after a smoke plume is no longer detectable by satellite, the results from the daily event study specification may not map directly to the average effect of a smoke event on air quality when measured over a longer time horizon. We therefore also estimate the relationship between smoke exposure and $PM_{2.5}$ at the quarterly level q, the time frequency of the labor market analysis, using the following regression, which later will also serve as the first stage of our IV estimation.

$$[PM_{2.5}]_{cq} = \beta \cdot SmokeDay_{cq} + \alpha_{c \times quarter\text{-}of\text{-}year} + \alpha_{state \times year} + \varepsilon_{cq}. \tag{3}$$

Wind patterns that carry wildfire smoke to a region may also bring in pollution from other sources. This does not necessarily pose an identification concern because even if this were the case, our research design would nevertheless capture the effects of pollution shocks driven by plausibly exogenous wind patterns. In this case, however, part of the effect we find could 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 the sensitivity of the daily $PM_{2.5}$ event study (Figure 2) to the inclusion of state- or county-specific wind direction bins in 60-degree increments. These flexible wind direction controls help us distinguish downwind wildfire pollution from generally dirty wind patterns. We conduct the same set of sensitivity checks for the quarterly labor market outcomes analysis (see Appendix Tables A.1 and A.2).

3.2 Wildfire Smoke and Labor Market Outcomes

We begin our analysis of the effects of pollution on labor market outcomes by analyzing reduced-form relationships between smoke exposure and labor market outcomes. The main estimation equation we implement is as follows:

$$\Delta Y_{cq} = \beta \cdot SmokeDay_{cq} + \alpha_{c \times quarter\text{-}of\text{-}year} + \alpha_{state \times year} + \varepsilon_{cq}, \tag{4}$$

where the outcome ΔY_{cq} is the change in the labor market outcome for county c in quarter q from the same quarter-of-year in the previous year. The focal dependent variable, $SmokeDay_{cq}$, counts the number of days that the county is fully covered by smoke plumes; thus, β reflects the effect of an additional day of wildfire smoke in the exposed county on the outcome variable. The remaining regression terms are as in equation (3). We weight regressions by county-year level population counts and two-way cluster standard errors at both the county and state-by-quarter levels. Unless noted otherwise, we use the same econometric specification as outlined in equation (4) throughout our analysis of the labor market effects of smoke exposure and air pollution.

Before proceeding, we wish to discuss two key features of the model. Our first comment regards the choice of using annual first difference in labor market outcome (ΔY_{ct}) as the dependent variable. Our study sample spans a 13-year horizon (2007-2019), covering the 2008-2009 recession and the subsequent decade when both income and employment were recovering. To control for differential time trends in the long panel, we measure labor market response as the *change* in earnings, employment, or LFP from year $t-1$ to t for the same county and the same quarter of the year. An alternative but less parsimonious approach is to use *levels* of labor market outcomes as the dependent variable while controlling for county-specific time trends in the regression. We report this as a robustness specification in Appendix Table A.1, along with specifications in which both the outcome and focal dependent variable are first-differenced.

Second, our specification effectively treats the panel unit of our study to be a county by the quarter of the year (e.g., Orange County in the summer). With the inclusion of the county-by-quarter-of-year fixed effects ($\alpha_{c\times quarter\text{-}of\text{-}year}$), our estimation equation exploits year-over-year variation in smoke days within the same county *and* during the same season of the year. Note that we do not exploit variation in smoke from one quarter to the next (e.g., comparing the first quarter of 2015 to the second quarter of 2015) because wildfire smoke follows seasonal patterns, with most smoke days concentrated in the summer and early fall. In addition, we include state-by-year fixed effects to control for state-specific common shocks and to capture time-varying changes, such as the Great Recession, at the state level.

We also perform a range of additional sensitivity checks on our specification choice. Because geographically larger counties have a lower probability of being fully covered by smoke, we conduct a robustness check in which the dependent focal dependent variable is the sum of the fraction of the county covered by smoke on each day in the quarter (Section 4.4). We also examine dynamic specifications by augmenting the main estimation equation (4) with two leads and two lags of $SmokeDays_{ct}$.[11] The dynamic specification coefficients on lagged smoke exposure describe whether the effects of smoke persist after the year of exposure. Coefficients on lead terms provide a "placebo" check on the effect of *next year's* smoke on *this year's* pollution and labor market responses, which we expect to be close to zero because outcomes should not be influenced by quasi-random future smoke shocks. A disadvantage of the dynamic specification is that we draw down the sample size as we add leads and lags of smoke exposure.

Next, we test whether the reduced-form relationships between outcomes and smoke exhibit a systematic, "dosage" pattern by exploiting variations in the cumulative number of days exposed in a given quarter. This is done by estimating a nonlinear version of the β coefficient in equation (4)

[11] The exact estimation equation we implement is $\Delta Y_{cq} = \beta_\tau \cdot \sum_{\tau\in[-2,2]} SmokeDay_{cq(y+\tau)} + \alpha_{c\times quarter\text{-}of\text{-}year} + \alpha_{state\times year} + \varepsilon_{cq}$ where $SmokeDay_{cq(y+\tau)}$ represents smoke exposure for the same county×quarter-of-year but during the τ^{th} year relative to the current year.

via a Frisch–Waugh–Lovell-style procedure: we first residualize both the outcome variable (ΔY_{cq}) and smoke exposure ($SmokeDay_{cq}$) by the fixed effects controls, and then calculate the averages of the residualized outcome by 10 equal bins of residualized smoke. The resulting nonlinear estimates illustrate how labor market outcomes respond to smoke shocks of varying intensity, thus providing an opportunity to test if the average effect of smoke (β) is driven by systematic relationships between exposure and outcomes, or by extreme, and potentially outlier, exposure events.

We explore the robustness of our results to a variety of additional specifications including alternative definitions of smoke exposure, the inclusion of flexible weather controls, alternative fixed effects controls, alternative data frequency (annual data analysis), alternative specifications of the outcome variable and time trends controls, and alternative standard error clustering choices. We repeat the same set of sensitivity checks with the IV estimation. We defer more details to Section 4.4 where we discuss these results.

3.3 Instrumental Variables Estimation

Drifting wildfire smoke provides a natural context to estimate the causal effect of air pollution on labor market outcomes using an instrumental variables (IV) framework. Consider the relationship between a labor market outcome Y_{cq} and ambient air quality as measured by $PM_{2.5}$ concentration, as given by the following equation:

$$\Delta Y_{cq} = \theta \cdot [PM2.5]_{cq} + \alpha_{c\times quarter\text{-}of\text{-}year} + \alpha_{state\times year} + e_{cq}. \tag{5}$$

If $[PM2.5]_{cq}$ is endogenous or measured with error, OLS will produce a biased estimate of θ, the effect of air pollution on labor market outcomes. To address these issues, we use an IV estimation strategy that leverages quasi-experimental variation in pollution driven by wildfire smoke exposure. Our first stage estimation equation is (repeating equation (3)):

$$[PM2.5]_{cq} = \beta \cdot SmokeDay_{cq} + \alpha_{c\times quarter\text{-}of\text{-}year} + \alpha_{state\times year} + \varepsilon_{cq}. \tag{6}$$

This is therefore a just-identified IV model with one excluded instrument ($SmokeDay_{cq}$), which we implement using the standard two-stage least squares (2SLS) estimation approach. A central identifying assumption for the IV approach is that the exclusion restriction holds. That is, we assume that, conditional on the fixed effects, the presence of wildfire smoke may only affect earnings, employment, and LFP through its impacts on air pollution. Our identification thus relies on the fact that an area's year-over-year variation in smoke exposure is driven largely by quasi-random factors (including the location and magnitude of fire events and shifting wind patterns), and it is unlikely to be correlated with unobservable determinants of labor market outcomes.

There are two potential counter-arguments to the exclusion restriction assumption. First, while quasi-random smoke shocks are unlikely to be correlated with economic determinants of labor market outcomes, they might interact with local atmospheric conditions, such as air temperature and precipitation, which can have independent impacts on worker productivity. In practice, we find that controlling flexibly for weather variables (by including bins of air temperature, precipitation, wind direction, and wind speed) has little impact on our smoke effect estimates. The inclusion of many weather controls, however, reduces the strength of the first stage of the IV estimation. In our main analysis, we have chosen to use the parsimonious specification with no weather controls, and we report sensitivity checks with weather controls in the Online Appendix.

A second concern involves the interpretation of the IV estimate as the causal effect of $PM_{2.5}$ specifically, as opposed to the effect of bad air quality in general as proxied by $PM_{2.5}$. Wildfire smoke contains a complex mix of air pollutants (e.g., Urbanski, Hao and Baker, 2008), and it is thus problematic to interpret the IV estimate to be the independent effect of any particular pollutant, an issue that pertains to many studies of the impact of air pollution. To illustrate the empirical variation, we examine the typical pollution mix of smoke exposure by repeating the daily event study analysis of equation (2) for six "criteria air pollutants" ($PM_{2.5}$, PM_{10}, O_3, CO, NO_2, and SO_2) recognized by the U.S. EPA to be among the most harmful to human health. To facilitate comparisons across different pollutants, we estimate the event studies in which the outcome is the measured concentration for each pollutant, standardized to have a mean of zero and a standard deviation (SD) of one. Appendix Figure A.3 shows that $PM_{2.5}$ exhibits the largest single-day spike on the smoke day by nearly 40 percent of a standard deviation. The next-largest increases are observed for PM_{10} and O_3, both increasing by over 25 percent of a standard deviation. Much smaller changes are observed for CO, NO_2, and SO_2 (less than 10 percent of a standard deviation). These results suggest that particulate matter is the signature emission of wildfires; at the same time, because all six pollutants show significant increases, caution should be taken attributing the effect of smoke on labor market outcomes to the independent effect of any particular pollutant.[12]

Finally, the relevance condition for IV estimation holds in our setting because smoke exposure is a strong predictor of ground-level air pollution. This is true both in the daily event study and at the quarterly level at which we conduct the main labor market analysis. As we report in more detail below, the first stage Kleibergen-Paap F-statistic is over 71 in our preferred IV specification.

4 Results

4.1 Air Quality Effects

Figure 2 reports the event study coefficients β_τ's of equation (2), which traces out the typical footprint of ground-level $PM_{2.5}$ levels in the 20 days before and 20 days after a smoke day. Smoke days are associated with elevated levels of $PM_{2.5}$ for four days, with an average increase of 2.19 $\mu g/m^3$ on the day of exposure, about one-third of a standard deviation in county-daily $PM_{2.5}$ concentrations.[13]

The relationship between smoke exposure and $PM_{2.5}$ can also be detected at the quarterly level, which is the time frequency at which we conduct the labor market analysis. Column (1) of Table 1,

[12] While it is difficult to find quasi-experimental variation of one pollutant while holding other pollutants constant, in Appendix Table A.3 we report the results of a multivariate OLS exercise that regresses earnings on multiple pollutants. We find evidence that $PM_{2.5}$ tends to be the most robust, negative predictor of earnings when estimated jointly with other pollutant(s) as covariates.

[13] In Figure 2, the mild increase in ground-level $PM_{2.5}$ on the day prior to a measured smoke day is likely due to the temporal frequency at which HMS smoke data were generated: satellites scan for smoke periodically during the daytime, whereas pollution monitors report a 24-hour average. So, when plumes move in overnight, they will show up as an increase in pollution at $t = -1$. This feature of the data represents a measurement error that is expected to attenuate our findings, as some of the non-smoke days in our data might in fact see mild increases in wildfire pollution.

Panel A, reports that increasing cumulative smoke exposure in the quarter by one day increases quarterly average $PM_{2.5}$ by 0.056 $\mu g/m^3$. This is equivalent to increasing $PM_{2.5}$ by 5 $\mu g/m^3$, or more than two times the single-day effect size. Consistent with the pattern of Figure 2, this also 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.

The magnitude of our estimates suggests most wildfire smoke events induce modest changes in air quality that are often not visible to the human eye. This underscores that our labor market estimates are not driven by a small number of days during which people are exposed to extremely intense smoke, which can generate substantial news coverage, possibly triggering behavioral responses that would not be present with normal sources of air pollution. Instead, the vast majority of smoke exposure days in our data lie within the normally experienced levels of air quality, helping to allay this concern. From Figure 2, smoke days are associated with increases of just over 2 $\mu g/m^3$ on the day of exposure relative to the daily mean of 10.2 $\mu g/m^3$. 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 $\mu g/m^3$, which are 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.

4.2 Earnings Effect

Panel A of Table 1 reports our main earnings effect estimate in column (1). Each day of wildfire smoke exposure in a county reduces per capita earnings by \$5.20 in the quarter, which represents a 0.097 percent reduction from quarterly mean earnings of \$5,359.70.

Panels B and C of Table 1 report OLS and IV estimates, respectively, of the effect of $PM_{2.5}$ on earnings. The number of observations decrease from those in Panel A because the estimation is restricted to counties with pollution monitoring data. Column (1) of Panel B shows that a one unit (1 $\mu g/m^3$) increase in quarterly $PM_{2.5}$ concentrations is associated with a significant reduction of \$10.6 in per capita quarterly earnings. Column (1) of Panel B shows that the IV estimate is

\$103.1 (representing a reduction of about 1.81 percent), an order of magnitude larger than the OLS estimate.

If one assumes that the effect of marginal smoke days reflects the average effect of all smoke days, our earnings estimates imply large effects of wildfire smoke on labor income at the national level. In 2010, approximately 160 million U.S. workers earned a total of \$6.4 trillion (in 2018 dollars). To estimate the total earnings losses from a typical year of smoke exposure, we multiply annual earnings by both the estimated reduction of 0.097 percent in earnings per day of smoke exposure and by the average number of smoke days per year (20.2) in our sample. This gives total earnings losses of \$125.4 billion (about 1.96 percent of annual earnings) per year of smoke exposure.

Another way to assess the magnitude of our results is to compare our IV estimates to the findings of prior studies on the effect of pollution on labor market outcomes. Studies in this area vary substantially in both research design and context, including the study country, time periods, industry focus, measures of labor market outcomes, the type of pollutants examined, and background pollution exposure levels. We make a simplifying choice and conduct comparisons using a measure of "pollution elasticity," that is, the percentage change in a labor market outcome per 1 percent change in the level of pollution being studied. Our analysis finds that a 1 $\mu g/m^3$ (approximately 10 percent) increase in quarterly $PM_{2.5}$ concentrations generates losses of per capita earnings amounting to \$103, or about 1.81 percent of quarterly earnings. The implied elasticity of our estimate is thus about -0.18.

Most prior work in this area focuses on the effect of short-term (daily or weekly) variation in air pollution on piece-rate workers. Graff Zivin and Neidell (2012) find that a 10 ppb increase in average ozone over a 9-hour period reduces output by 5.5 percent among outdoor fruit packers in California (an elasticity of -0.26). Chang et al. (2016) show that a 10 $\mu g/m^3$ increase in daily $PM_{2.5}$ leads to a 6 percent output reduction for indoor fruit packers in California (an elasticity of -0.062). Chang et al. (2019) study call center workers in a large urban city in China and find a 10 unit increase in the city's daily Air Pollution Index leads to a decrease of 0.35 percent in worker output (an elasticity of -0.023). Adhvaryu, Kala and Nyshadham (2022) study the effects on garment manufacturing workers in India, showing each 10 unit increase in hourly $PM_{2.5}$ reduces worker output by 0.5 percent (an elasticity of -0.052). He, Liu and Salvo (2018) use data on textile manufacturing workers in a heavily polluted industrial town in China and show an output reduction of 1 percent per 10 $\mu g/m^3$ $PM_{2.5}$ of sustained exposure during the previous month (an elasticity of -0.30). Aragón, Miranda and Oliva (2017) examine weekly household survey data in Peru and document a 2 percent reduction of weekly hours worked per 10 percent increase in $PM_{2.5}$ exposure in the previous week (an elasticity of -0.20).

Relatively fewer studies have examined longer-term effects of pollution exposure that leverages annual or permanent changes. Hanna and Oliva (2015) leverage changes in air pollution due to the closure of a large refinery in Mexico City and estimate that a 10 percent decrease in SO_2 concentrations increased hours worked by 1.5 percent (an elasticity of -0.15). Fu, Viard and Zhang (2021) study a nationwide sample of manufacturing firms in China and show a 0.44 percent reduction in firms' yearly productivity (measured by value added per worker) per 1 percent increase in $PM_{2.5}$ in the year (an elasticity of -0.44). Isen, Rossin-Slater and Walker (2017) exploit regulations of total suspended particulates (TSP) under the 1970 Clean Air Act and estimate that a 10 percent increase in exposure to TSP in childhood has negative effects on income levels 30 years later, with earnings about 1 percent lower (an elasticity of -0.10).

Though our study differs from each of these prior studies in many respects, the elasticity of -0.18 that we find is the same as the average elasticity of -0.18 across these 9 prior studies. Our findings are based on national data covering income from nearly every industry, while many of the prior studies focused on narrower industry or output categories; thus, the similarity in findings suggests that air pollution affects labor markets broadly, and not just in narrowly defined settings.

4.3 Extensive Margin Responses

Next, we examine 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 the labor supply, or may even cause workers to leave the labor force altogether. Second, diminished health, whether temporary or chronic, may affect one's opportunities in the labor market. 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 of labor force attachment.

We use equation (4) to test for extensive margin responses to smoke exposure. We first estimate the effect of smoke on employment as measured by the QWI. In Table 1, column (3) of Panel A reports that each day of wildfire smoke reduces quarterly employment in the county by 79.6 per million individuals aged 16 and over, a 0.013 percent decline relative to the sample average employment rate of 62.6 percent. Furthermore, as reported in column (4) of Panel A, each day of wildfire smoke reduces LFP in the county by 38.7 per million people.

The extensive margin results provide additional support for a conclusion of significant income losses due to smoke exposure. If those who lose employment earn average incomes, and if the reduction in labor supply lasts one quarter, the employment effects of a day of smoke exposure would reduce quarterly income by 0.013 percent. By comparison, each day of smoke exposure reduces quarterly income by 0.097 percent (Table 1, Panel A, column (2)). Thus, the employment reductions due to smoke can account for over 13 percent (0.013/0.097) of the total income effect of smoke exposure. This calculation illustrates the potential for relatively small but recurring shocks to employment to have sizeable effects on total earnings.

4.4 Robustness Checks

Dynamic specification. In Figure 3, for each of the four outcomes ($PM_{2.5}$, earnings, employment, and LFP), we report dynamic specifications that include the effect of the next years' exposure to smoke on this year's outcome (thus describing effects in event years $t-1$ and $t-2$, providing a placebo check) and the lagged effects of previous years' exposure to smoke (describing effects in event years $t+1$ and $t+2$).

The patterns in Figure 3 reveal significant effects of smoke in the year of exposure (event year t). Panels A and B suggest that each day of smoke exposure leads to an increase in $PM_{2.5}$ of 0.053 $\mu g/m^3$ (p-value < 0.01) and earnings losses of \$7.50 per capita (p-value < 0.01). On the same graph, we superimpose the static estimates from Panel A of Table 1. Overall, the dynamic estimates for year t resemble their static counterparts. The small point estimates of the effects of smoke in event years $t+1$ and $t+2$ suggest that the earnings effects of smoke do not have significant lags, but instead are concentrated during the year of exposure. Moreover, the estimated effects of future smoke in event years $t-1$ and $t-2$ are negligible, consistent with quasi-random smoke exposure events. In the case of LFP, the year t coefficient is no longer statistically significant once conditional on the leads and lags of exposure; the dynamic pattern of LFP effects aligns with those of the earnings and employment effects but it is more noisily estimated.

Nonlinear specification. Figure 4 reports the decile bin scatterplot of the first-stage and reduced-form estimates in Panel A of Table 1. By construction, the slopes of the superimposed linear fit lines equal the corresponding coefficients in Table 1. We find that $PM_{2.5}$ and earnings effects are approximately linear in the number of days of smoke in a quarter. The patterns for the employment and LFP effects are relatively less clear-cut, although we cannot reject a linear relationship in either case. Overall, we conclude that the labor market effects we identify in this paper are driven by typical pollution shocks rather than by a few extreme exposure events.

Other robustness specifications. We report a series of additional robustness checks in Appendix Table A.1. In Panel A, we recode county's smoke exposure on any given day as the fraction of the county's land area covered by smoke plumes (rather than by an indicator for whether the county is entirely covered); we then build the quarterly smoke measure by adding up these fractions. In Panel B, we estimate models with flexible weather controls. Regressions in the first row include 10-degree Fahrenheit bins of daily temperature, decile bins of quarterly total precipitation, 60-degree angle bins of daily prevailing wind direction, and decile bins of daily average wind speed. The second and third rows include wind direction controls fully interacted with state and county fixed effects (see discussion in Section 3.1). In Panel C, we test sensitivity to fixed effects strategies by replacing the state-by-year fixed effects with Census Division-by-year fixed effects (the second row), Census Region-by-year fixed effects (the third row), and year fixed effects (the fourth row). Note that the relaxation of fixed effects controls increases the overall amount of variation used in the estimation, but potentially introduces bias if regional smoke trends are correlated with labor market trends. In Panel D, we aggregate quarterly pollution and labor market outcomes to a yearly frequency and estimate the effect of smoke exposure on outcomes at the annual level. In Panel E, we report specifications with levels of labor market outcomes (instead of first differences) as the dependent variables, both with and without county-specific linear time trends controls; we also report robustness specifications in which all labor market outcomes, pollution, and smoke variables are first differenced. In Panel F, we vary our choice of standard errors clustering in various ways. In Appendix Table A.2, we repeat the same set of robustness checks with the IV model.

Our findings are generally robust across these specifications, but we mention a few exceptions from Appendix Table A.1. Panel C shows that, in the quarterly analysis, results change little whether controlling for time patterns (year fixed effects) that are allowed to vary at the state, Census Division, Census Region, or national levels. However, as shown in Panel D, annual-level regressions are more sensitive to this choice. The second row of Panel E reports that the estimated effects on earnings and employment become smaller and change sign, respectively, in a model in which the outcomes are specified in levels and in which county time trends are omitted. Both sets of findings indicate that while it is important to account for region-specific time trends in the analysis, various ways of doing so produce similar findings.

Migration responses. Another potential concern is whether smoke exposure may change the underlying population composition. We believe this is unlikely because smoke exposure causes transient, modest changes in daily air pollution. To directly test whether year-over-year changes in smoke affect migration into and out of a county, we use the Internal Revenue Service (IRS) Statistics of Income (SOI) county-to-county population flow data to measure in-migration and out-migration at an annual frequency. We also measure changes in population size using the total number of tax exemptions claimed in an area. The results, reported in Appendix Table A.4, 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.

4.5 IV Estimates by Age and Industry

In this section, we report IV estimates of the effect of $PM_{2.5}$ on earnings by age and industry. This analysis leverages the QWI's earnings breakdown by 10-year age groups (25-34, 35-44, 45-54, 55-64, and 65 and older) and two-digit NAICS sectors. The estimation follows exactly the 2SLS steps outlined in equations (5) and (6), except that in age group-specific IV estimation we replace all-age population weights by the population of the corresponding age group.

Panel A of Figure 5 reports estimated earnings effects separately by age groups. We find that $PM_{2.5}$ reduces earnings across all age groups. Not surprisingly, larger absolute effects emerge for middle-age workers who earned the most.[14] However, we also detect precise and disproportionate earnings losses due to pollution for elderly workers. On a percentage basis, the largest earnings response to pollution is observed for individuals aged 65 and older. Because the health of older workers may be more sensitive to pollution shocks, smoke effects may be strongest among older workers, potentially generating losses associated with labor market transitions and retirements.

Panel B of Figure 5 reports heterogeneity across 20 industries, as delineated by the 2-digit NAICS code. To adjust for multiple hypothesis testing, we control for the family-wise error rate based on 100 bootstraps of the free step-down procedure of Westfall and Young (1993), as implemented by Jones, Molitor and Reif (2019). The figure highlights industries with an adjusted p-value less than 0.05.

We point out two connections between our industry-specific results and the prior literature.

[14] Average quarterly earnings for each age group are as follows: \$7,178 (ages 25–34), \$10,203 (ages 35–44), \$10,796 (ages 45–54), \$8,342 (ages 55–64), and \$1,671 (ages 65 and above).

First, we find that manufacturing is among the most responsive industry to air pollution shocks. Each 1 $\mu g/m^3$ increase in quarterly $PM_{2.5}$ reduces earnings by 2.4 percent, which implies an elasticity of -0.24. As we discussed in Section 4.2, a significant share of the prior literature has examined the effect of air pollution on labor market outcomes in the manufacturing sector. Perhaps the closest study in terms of scale is Fu, Viard and Zhang (2021), who found an annual pollution-productivity elasticity of -0.44 among a large sample of firms the Chinese manufacturing sector. Other studies that use high-frequency output measures of manufacturing workers in various contexts have found pollution elasticities ranging from -0.05 to -0.30 (Aragón, Miranda and Oliva, 2017; He, Liu and Salvo, 2018; Adhvaryu, Kala and Nyshadham, 2022). Our manufacturing sector estimate is therefore broadly in line with the prior literature.

Second, we find little evidence that air pollution reduces earnings in the overall agricultural sector. In contrast, some of the pioneering work in this field has established a significant link between day-to-day changes in air pollution and a reduction in productivity among piece-rate agricultural workers such as fruit packers (Graff Zivin and Neidell, 2012; Chang et al., 2016). One potential explanation is that the agriculture sector in our data is very broadly defined, spanning sectors such as crop and animal production, logging, and fishing. To further investigate the difference, we use QWI data's three-digit NAICS breakdown to estimate separate pollution effects for the five subsectors of the agricultural industry: crop production (NAICS 111), animal production and aquaculture (NAICS 112), forestry and logging (NAICS 113), fishing, hunting and trapping (NAICS 114), and support activities for agriculture and forestry (NAICS 115). Because earnings are not available at three-digit NAICS level, we instead use employment as the outcome measure for this analysis. Appendix Table A.5 reports IV estimates by agricultural subsector. Column (1) shows a statistically insignificant effect of air pollution on the overall agricultural sector. However, breaking this effect down by subsector reveals concentrated effects for crop production (column (2)); precise zeroes for animal production, forestry and logging, and fishing and hunting (columns (3)–(5)); and negative but imprecise effects for support activities (column (6)). The effect we detect for crop production, which includes most farming activities, broadly aligns with the findings of the prior literature on agricultural workers. The magnitude of the crop sector effect has an implied pollution elasticity of -0.18. By comparison, Graff Zivin and Neidell (2012) examine the influence of day-to-day fluctuation of ozone pollution on daily productivity among pear packers and find an implied ozone elasticity of -0.26.

Beyond manufacturing and agricultural, our estimates also reveal significant negative earnings effects of pollution exposure in other sectors, such as utilities, health care, real estate, administration, and transportation. We find no evidence that any sector experienced significant increases in earnings in response to pollution exposure. However, more research is needed to understand why certain sectors are more vulnerable to pollution exposure than others.

4.6 Heterogeneity by County Characteristics

To shed light on the conditions under which labor markets are the most sensitive to pollution shocks, we explore how the effects of wildfire pollution vary with county characteristics. To do this, we create indicators for whether a county is above- or below the median with respect to each of five characteristics: urban population share, fraction of population in poverty, median home value, Black population share, and the sample average $PM_{2.5}$ concentration (as a proxy for the area's general air quality). For each characteristic, we estimate heterogeneity in the earnings effects of smoke exposure using an augmented version of equation (4) that fully interacts the smoke exposure variable with an indicator for whether the county is above the median for the characteristic.

Table 2 reports the results of this heterogeneity analysis. Columns (1)–(5) report separate regressions in which we examine heterogeneity with respect to one characteristic at a time. Column (6) reports a joint regression in which the interaction terms with all five characteristics are included simultaneously. Among the characteristics we examine, the only statistically significant margin of heterogeneity emerges for the racial composition of the county (column (4)). The point estimates suggest that smoke-induced declines in earnings are about 59 percent larger in counties that have an above-median proportion of Blacks. We obtain similar results in the joint estimation of column (6) which, in addition to the heterogeneity finding on racial composition, suggests that smoke causes more declines in earnings in less-urban areas, although the point estimate is only marginally significant (p-value < 0.10).

5 Welfare

5.1 Air Pollution and Welfare

In this section, we provide a back-of-the-envelope calculation on the social welfare costs associated with lost earnings due to wildfire smoke exposure, and we compare this to the welfare costs 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 preexisting 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 if they are forced into early retirement by smoke-related illness.

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 preexisting 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 reduce deadweight loss by an amount that equals the change in labor times 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 percent to calculate that welfare increases by one-quarter of the total loss, or \$31 billion of the \$125 billion.

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 1. 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 the longer-run losses of 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 reveals that a wage change leads to a welfare loss proportional 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 to calibrate the appropriate scaling of the earnings losses.

Absent detailed data on time use and illness, some assumptions are required 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 losses reflect true costs to the worker.

Social welfare. Social welfare combines both individual welfare losses and changes in deadweight loss from taxation. In the case in which 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.[15] Assuming a marginal tax rate of 25 percent and $\eta_{h,w} = 0.5$ implies a social welfare effect of 75 percent (two-thirds from labor supply plus one-twelfth from deadweight loss) of lost earnings.

Applying the above model to the estimates reported in Table 1, we find that the welfare losses working through labor market responses are $94 billion in 2018 dollars. The lasting damage to labor market opportunities shows up as lower wages; this 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. Losses may approach an upper bound of $125 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 percent of lost earnings, or $31 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.

The calculation above focuses on the cost of wildfire smoke exposure. To facilitate our discussion in the next subsection, we also use our IV estimate to quantify the welfare impact of a unit increase in $PM_{2.5}$. Our preferred IV estimate in Table 1 shows a quarterly loss of per capita earnings of $103 per one unit increase in $PM_{2.5}$. Extrapolated to the annual level, this estimate im-

[15]Intuitively, lost earnings that arise from a 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.

plies a per capita earnings loss of \$412, or a national total of \$123 billion. Our preferred estimate of the social welfare loss of a 1 $\mu g/m^3$ increase in $PM_{2.5}$ is thus about \$92 billion per year. Our lower-bound estimate of the welfare effect (25 percent of lost earnings) is \$31 billion per year.[16]

5.2 Comparison with Mortality Costs

We now evaluate the importance of incorporating labor market effects into estimates of air pollution costs by benchmarking the costs of lost earnings to those of premature deaths due to pollution. We draw causal $PM_{2.5}$-mortality estimates from Deryugina et al. (2019), who show that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ for one day causes 0.69 additional deaths per million elderly individuals aged 65 and up over the next three days, representing a 0.18 percent increase relative to the average 3-day mortality rate of the study population. Scaling the daily mortality effects linearly to the annual level, this estimate implies that a 1 $\mu g/m^3$ increase in annual $PM_{2.5}$ causes 3,383 additional deaths annually among the 40.3 million people 65 and older in 2010.

To convert the number of premature deaths to a mortality cost, we consider two alternative value of statistical life (VSL) estimates. First, the EPA uses a value of \$9.25 million (in 2018 dollars) per statistical life regardless of population characteristics such as age, implying annual mortality costs of \$31.3 billion. Second, we use a more conservative 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 dollars by the average remaining life expectancy of 16.1 years among this population.[17] This second VSL value implies annual mortality costs of \$8.1 billion.

In additional analyses reported in the Online Appendix, we also consider a complementary approach to benchmark the costs of lost earnings to those of premature deaths by directly estimating the effect of smoke on mortality. Using county-monthly mortality data from the National

[16] Implicitly, we consider a homogeneous treatment effects model to extrapolate from our estimates to annual, national effects. Alternatively, our estimates can be interpreted as a local average treatment effect (LATE) for the compliers—those counties that see an increase in particulate matter due to smoke exposure.

[17] 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).

Vital Statistics System, we show that smoke exposure elevates elderly mortality, with an implied mortality cost of \$5.2 billion to \$19.9 billion annually per 1 $\mu g/m^3$ increase in $PM_{2.5}$—a finding that is similar to the estimate we derive using Deryugina et al. (2019) as the basis of our calculations. The mortality effects we estimate are noisy, however, when we aggregate the analysis to the quarterly frequency, the temporal level of our labor market analysis. We relegate full details of this analysis to the Online Appendix and use mortality costs derived from Deryugina et al. (2019) as our preferred estimate.

To sum up, we find that the annual mortality costs of air pollution (\$8.1 billion to \$31.3 billion per 1 $\mu g/m^3$ increase in $PM_{2.5}$) are lower than the lost labor market earnings (\$123 billion) and similar to or lower than our preferred estimate of \$92 billion in welfare costs of these lost earnings. Even our lower bound of \$31 billion in welfare costs due to lost earnings is on par with the highest estimates of the mortality costs. While these calculations are imprecise in nature and are only intended to facilitate an order-of-magnitude comparison, they suggest that labor market responses comprise a large share of the welfare costs of wildfire smoke, and that such costs should be taken into account when evaluating the overall costs of air pollution and efforts to limit it.

6 Discussion and Conclusion

Wildfires emit large amounts of smoke that contains harmful pollutants and can drift for hundreds or thousands of miles, regularly affecting populations far from the fires themselves. We analyze variation in wildfire smoke exposure across the United States and find that increases in smoke exposure cause significant decreases in earnings and employment outcomes. We leverage plausibly exogenous variation in smoke exposure to produce national estimates of the causal effects of air pollution on labor market outcomes. Our analysis suggests that the welfare costs of lost earnings is similar to or larger than the costs of increased mortality due to wildfire smoke. 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 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 that 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 gains in workers' earnings and employment, 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. Decisions about land use and fire management in one location can affect those living in distant regions. These widespread effects call for greater coordination of fire policies, including a focus on preventing the start and spread of wildfires. Policies should consider factors that go beyond traditional goals of defending land and property exposed to fires in a given region to incorporate issues such as the amount of smoke produced by the fire and whether the smoke plumes may reach areas with large populations. 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 to the extent possible. 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, policies could better mitigate damages from these events by assessing the full scope of their effects.

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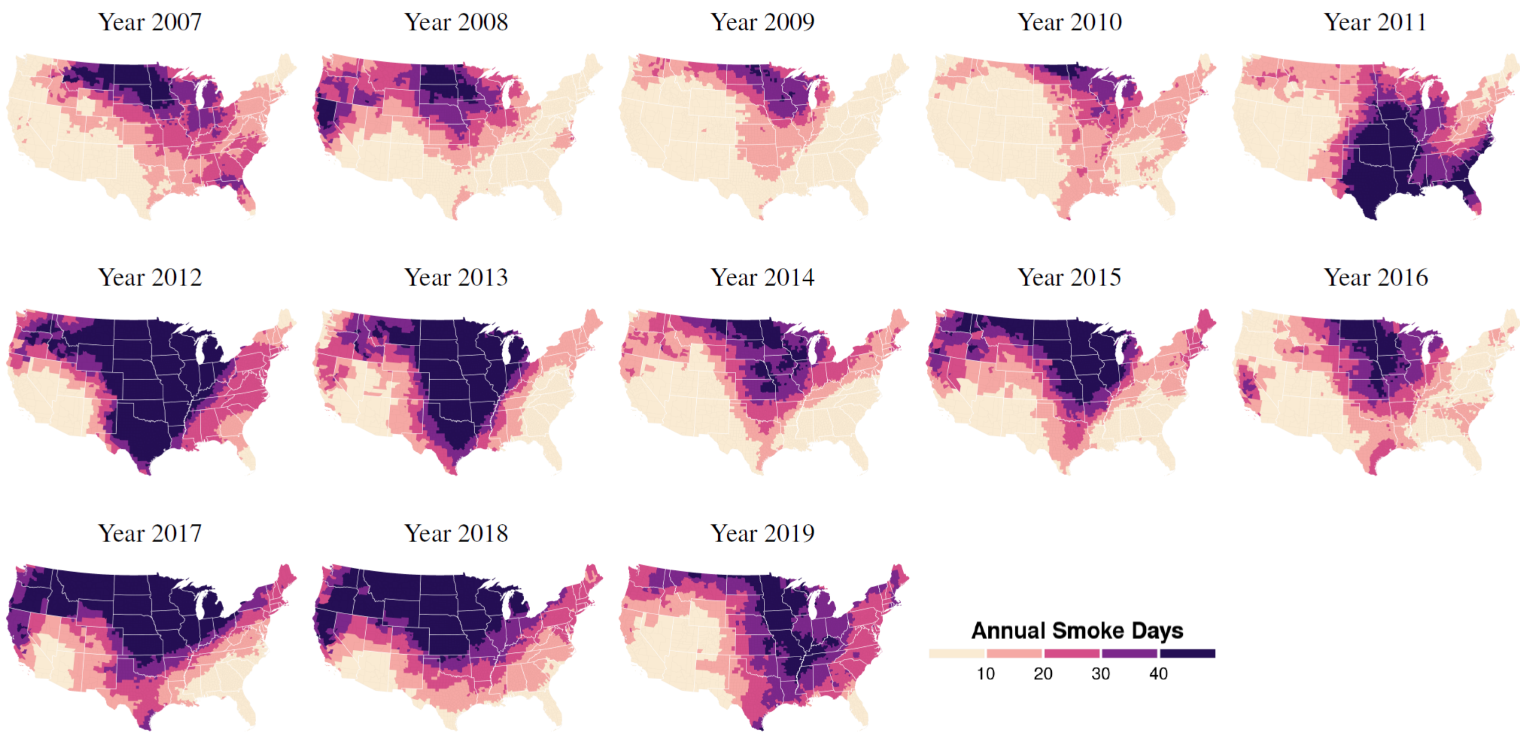
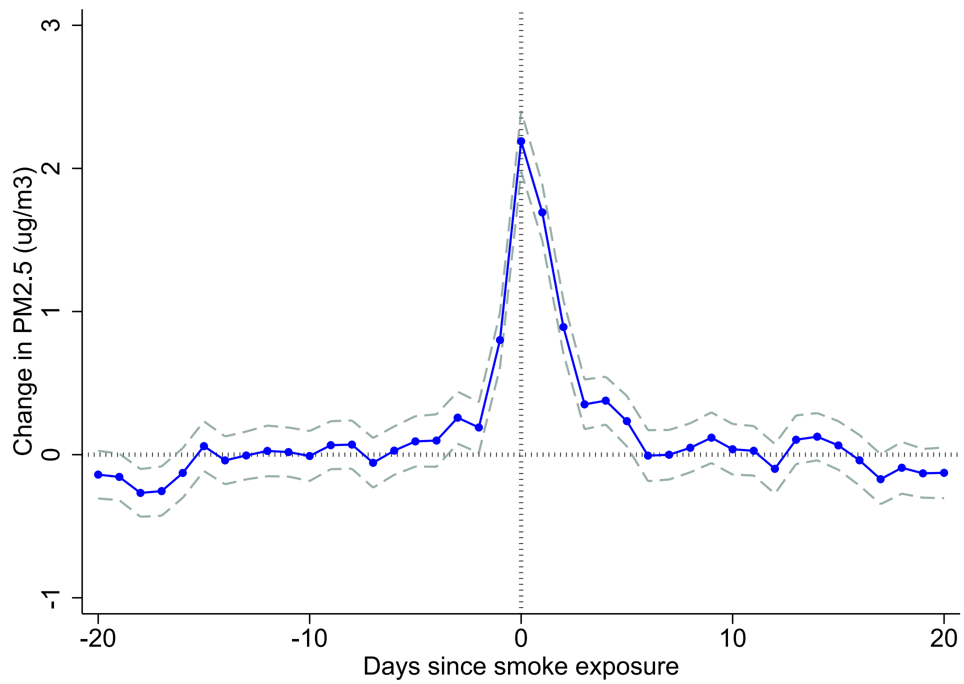
Figure 1: Annual Number of Smoke Days



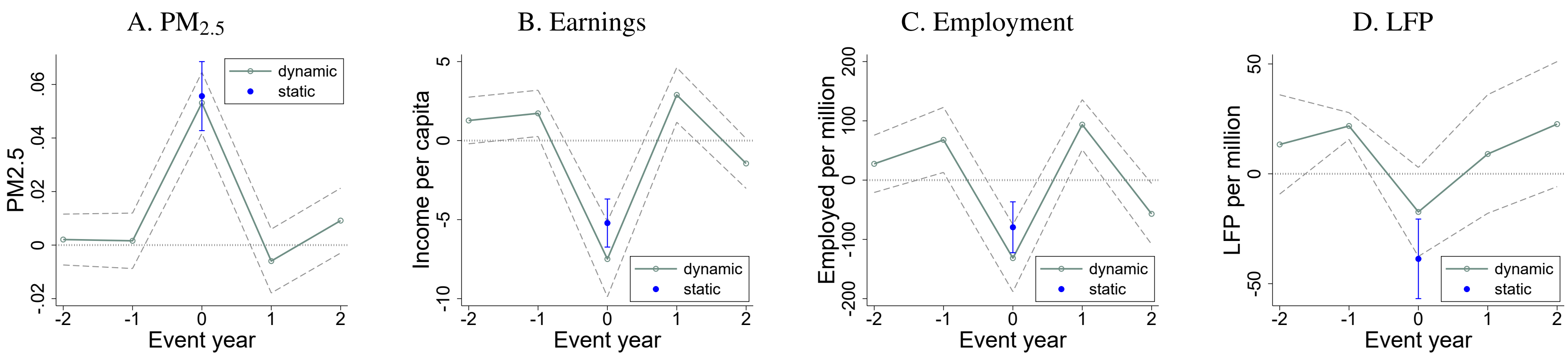
Notes: This figure plots the number of days of smoke exposure in each county in the continental United States over the 2007-2019 sample period. Average population-weighted exposure during this period was 20.2 days per year.

Figure 2: Wildfire Smoke and Ground-Level $PM_{2.5}$: Daily Event Study



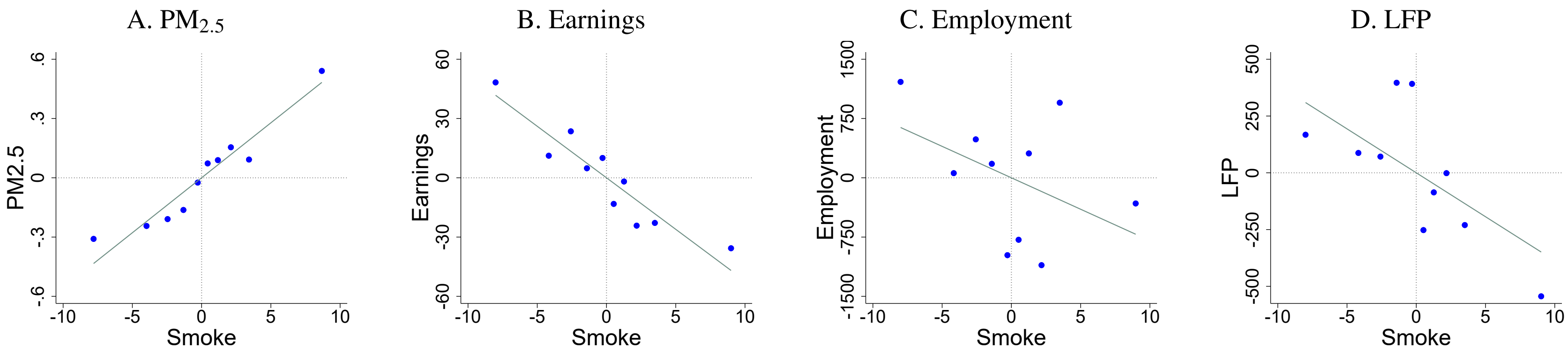
Notes: This figure shows coefficients from a regression of daily $PM_{2.5}$ on indicators of daily smoke exposure up to 20 days before and after the day of observation. In addition to the 41 smoke indicators, the regression controls for county-by-day-of-year fixed effects and state-by-year fixed effects. Standard errors are clustered at both the county and the date levels.

Figure 3: Labor Market Effects of Wildfire Smoke: Static vs. Dynamic Estimates



Notes: We augment the baseline regressions of Table 1, Panel A with two lead and two lag terms of smoke exposure. The baseline estimates (labeled "static") are superimposed for comparison. All regressions are weighted by county population (panels A, B, and D) and population over age 16 (panel C), and include county-by-quarter-of-year fixed effects and state$\times$year fixed effects. Standard errors are two-way clustered at the county and state-by-quarter levels.

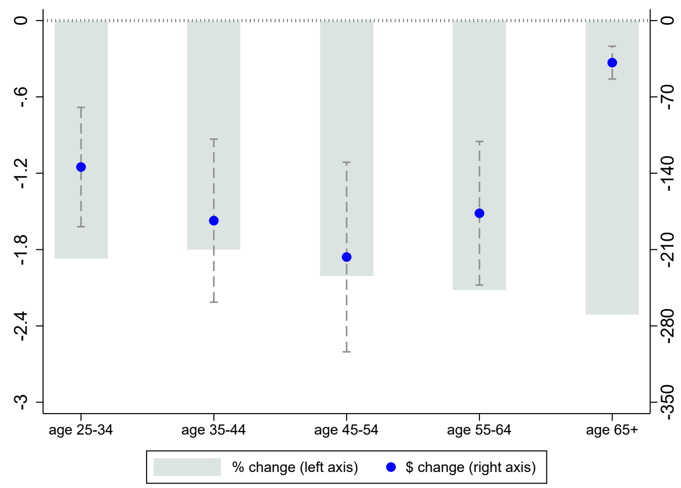
Figure 4: Labor Market Effects of Wildfire Smoke: Linear vs. Nonlinear Estimates



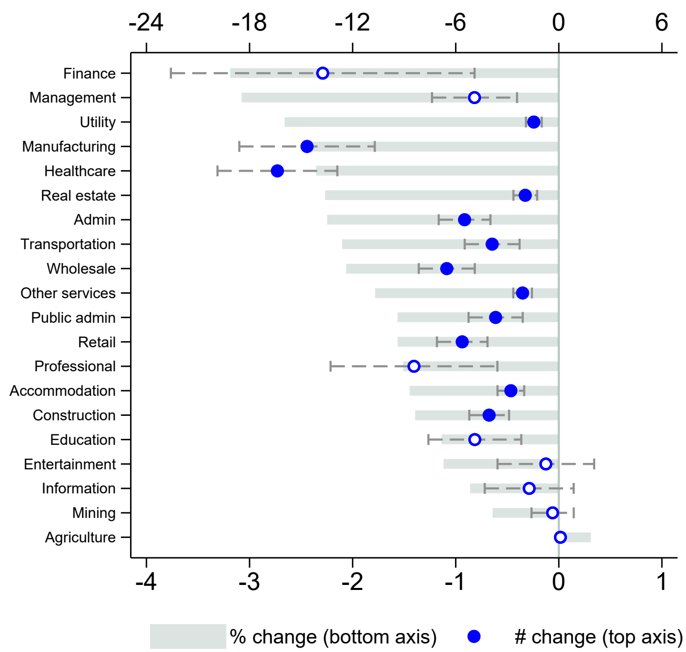
Notes: We residualize outcome variables and smoke exposure by county-by-quarter-of-year fixed effects and state-by-year fixed effects, and then plot a decile binscatter of residualized outcome by residualized smoke. Regressions are weighted by county population (panels A, B, and D) and population over age 16 (panel C). Slopes of the superimposed linear fit lines represent OLS regression coefficients as reported in Panel A of Table 1.

Figure 5: IV Estimation by Subgroups

A. By age group



B. By industry sector



Notes: Point estimates and range plots show the estimates in levels; bars convert the level estimates to percentage terms by dividing the estimates by the average per capita earnings of the corresponding group. Regressions in Panel A are each weighted by county population in the corresponding age groups. Average quarterly earnings for each age group are as follows: \$7,178 (ages 25–34), \$10,203 (ages 35–44), \$10,796 (ages 45–54), \$8,342 (ages 55–64), and \$1,671 (ages 65 and above). Regressions in Panel B are weighted by county total population. In Panel B, solid points highlight industries with a family-wise adjusted p-value of less than 0.05 based on 100 bootstraps of the free step-down procedure of Westfall and Young (1993). All regressions include county-by-quarter-of-year fixed effects and state-by-year fixed effects. Standard errors are two-way clustered at the county and state-by-quarter levels.

Table 1: Wildfire Smoke, Pollution, and Labor-market Outcomes

	(1) $PM_{2.5}$	(2) earnings	(3) employment	(4) LFP
A. First-stage and reduced-form estimates				
Smoke	0.056***	-5.217***	-79.6***	-38.7***
	(0.007)	(0.776)	(21.9)	(9.2)
Outcome mean	9.46	5,359.7	625,776	625,434
Observations	75,207	160,346	160,346	161,498
B. OLS estimates				
$PM_{2.5}$	–	-10.566***	-261.0**	-95.7*
	–	(3.089)	(113.9)	(54.7)
Outcome mean	–	5,687.6	643,597	631,806
Observations	–	74,725	74,725	75,193
C. IV estimates				
$\hat{PM}_{2.5}$	–	-103.1***	-1750.1***	-790.9***
	–	(20.4)	(434.8)	(182.1)
Kleibergen-Paap F	–	71.8	71.2	71.7
Outcome mean	–	5,687.6	643,597	631,806
Observations	–	74,725	74,725	75,193

Notes: An observation is a county-quarter. The smoke variable (the focal dependent variable in Panel A) counts the number of days a county is fully covered by a wildfire-smoke plume in a quarter. In Panel C, the smoke variable is used as an instrument for a county's quarterly average $PM_{2.5}$. In all panels, the outcome mean reports the mean of the dependent variable before first differencing. All regressions are weighted by county population (columns 1, 2, and 4) and population over age 16 (column 3), and include county-by-quarter-of-year fixed effects and state-by-year fixed effects. Standard errors are two-way clustered at the county and state-by-quarter levels. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 2: Wildfire Smoke and Earnings: Heterogeneity by County Characteristics

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

Notes: Each column is a separate regression. Indicator variables flag counties with above median: fraction of urban population (Census 2010), fraction of population living under 100% of the Federal Poverty Line (ACS 2007-2016), county median home value (ACS 2007-2016), share of African American population (ACS 2007-2016), and sample-average PM_2.5. All regressions are weighted by county population, and include county-by-quarter-of-year fixed effects and state-by-year fixed effects. Standard errors are two-way clustered at the county and state-by-quarter levels. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Online Appendix

Air Pollution and the Labor Market: Evidence from Wildfire Smoke

Mark Borschulte, David Molitor, & Eric Yongchen Zou

Appendix A: Mortality Effects Estimation

In Section 5.2, we calculate mortality costs of air pollution using established estimates from Deryugina et al. (2019). Here we consider a complementary approach to benchmark the costs of lost earnings to those of premature deaths by directly estimating the effect of smoke (and the resulting pollution increases) on mortality. A conceptual appeal of this approach is that we rely on the same source of variation in deriving the mortality damages as we did in deriving the earnings losses, facilitating a direct comparison of labor market and mortality costs of pollution.

We measure mortality outcomes using 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 from 2007 to 2015.

We begin by estimating the mortality effect of smoke exposure at the monthly level, the temporal level of our mortality data, using a regression specification that mirrors that from our earnings analysis. The outcome, $Mortality_{cm}$, is measured as deaths per million in county c and month m. We regress this outcome on the number of days $SmokeDay_{cm}$ in which the county was exposed to wildfire smoke that month:

$$Mortality_{cm} = \beta \cdot SmokeDay_{cm} + \alpha_{c\times month\text{-}of\text{-}year} + \alpha_{state\times year} + \varepsilon_{cm}. \tag{A–1}$$

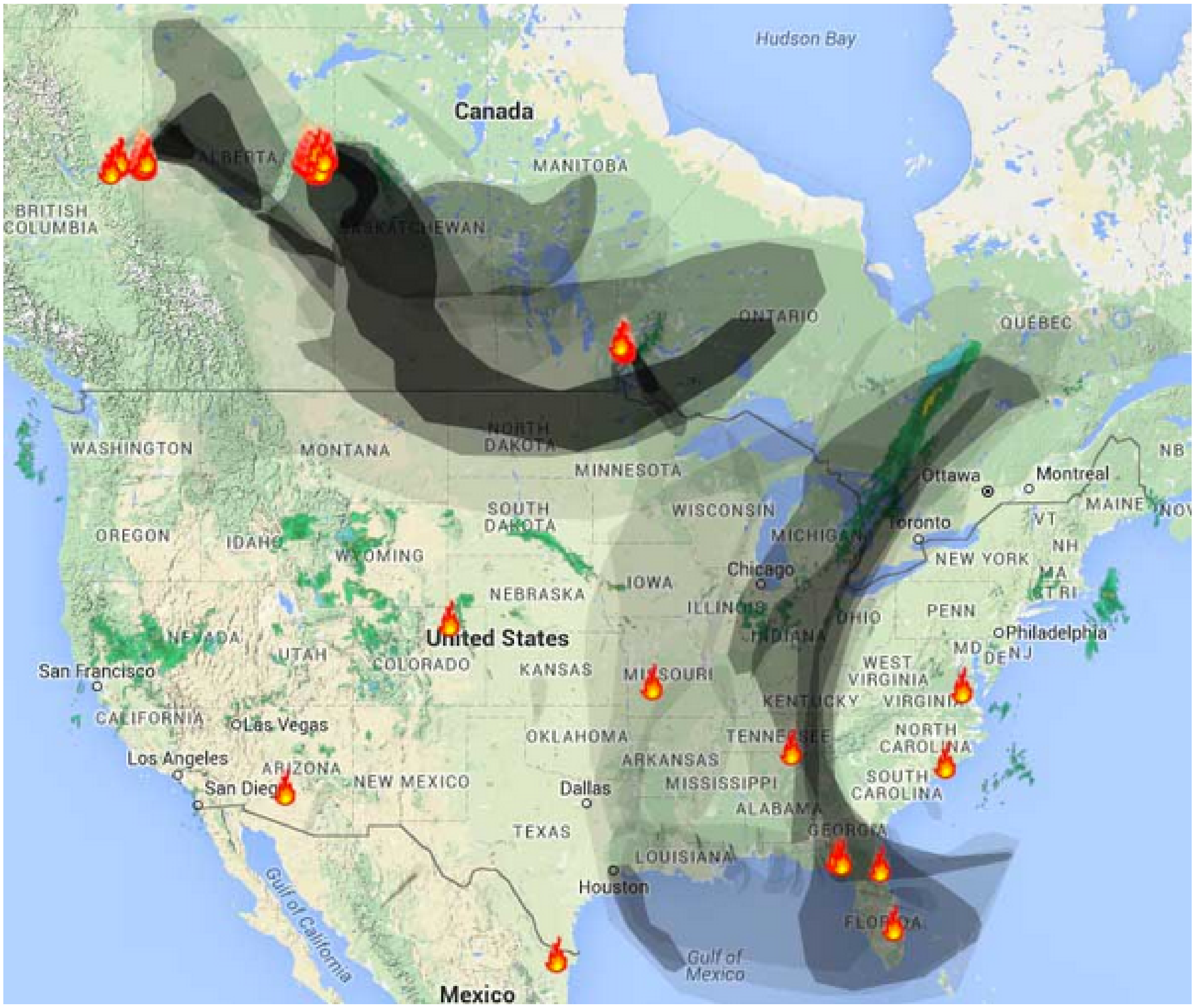
The primary coefficient of interest is β, which describes the effect of an additional day of smoke on mortality in the month of exposure. Analogous to equation (4) we include county-by-month-of-year fixed effects and state-by-year fixed effects to control for county-specific seasonality as well as common shocks at the state-year level. Standard errors are two-way clustered at the county and state by month levels. Like in the labor market analysis, we also report OLS regressions in which we use monthly average $PM_{2.5}$ concentration as the key independent variable in equation (A–1). We further implement IV models instrumenting for monthly $PM_{2.5}$ using $SmokeDay_{cm}$.

Panel A of Appendix Table A.6 reports the estimates for all age groups (column (1)), the non-elderly group (column (2)), and the elderly population (column (3)). The mortality estimates allow us to compare the costs of mortality to social welfare losses of a 1 unit increase in $PM_{2.5}$, now using IV estimates that come directly out of the smoke quasi-experiment. Column (3), Panel A shows that each day of smoke in a month increases the elderly mortality rate by 0.972 deaths per million people. This estimate has a standard error of 0.522 and is marginally significant at the 10 percent level. The corresponding IV estimate is noisily estimated, and suggests a unit increase in monthly $PM_{2.5}$ increases elderly mortality by 4.45 deaths per million (SE=3.34, p-value=0.183), or an annual effect of 53.4 additional deaths per million people. The magnitude of our monthly $PM_{2.5}$-mortality IV estimate is comparable to the three-day mortality effects reported in Deryugina et al. (2019) who also study the elderly population during a similar period. The implied monthly effect of a 1 $\mu g/m^3$ $PM_{2.5}$ on elderly mortality is $(0.69 \div 3) \times 30 = 6.9$ deaths per million. Using the two VSL approaches mentioned in Section 5.2, we conclude that the annual mortality cost among the elderly is \$5.2 billion to \$19.9 billion. If we instead use the all-age IV estimate of 0.379 deaths per million people for the calculation (Table A.6, Panel A, column (1)), the implied mortality cost based on the EPA's VSL estimate of \$9.25 million per life lost is \$13 billion annually.

In Panel B of Appendix Table A.6, we repeat reduced-form, OLS, and IV models but aggregating data at the monthly level to the quarterly level, the temporal level of our labor market analysis. Unfortunately, standard errors in the quarterly estimates are too large to draw conclusions. These noisy results may partially reflect well-known challenges of estimating the effect of transient pollution changes on longer-run mortality outcome due to issues such as harvesting and behavioral responses. Most of the existing literature we are aware of focuses on either the pollution's effect in the short run (e.g., Knittel, Miller and Sanders, 2016; Schlenker and Walker, 2016; Deryugina et al., 2019), or on the longer-run mortality effects of sustained pollution exposure (e.g., Deschênes, Greenstone and Shapiro, 2017; Anderson, 2020; Ebenstein, Lavy and Roth, 2016).

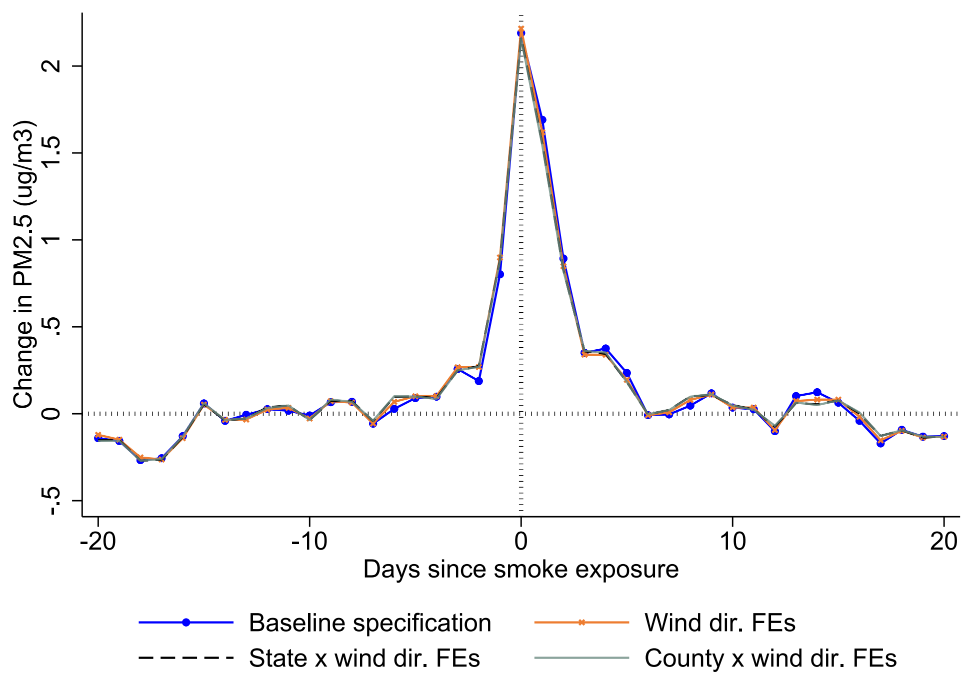
Appendix Figures and Tables

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



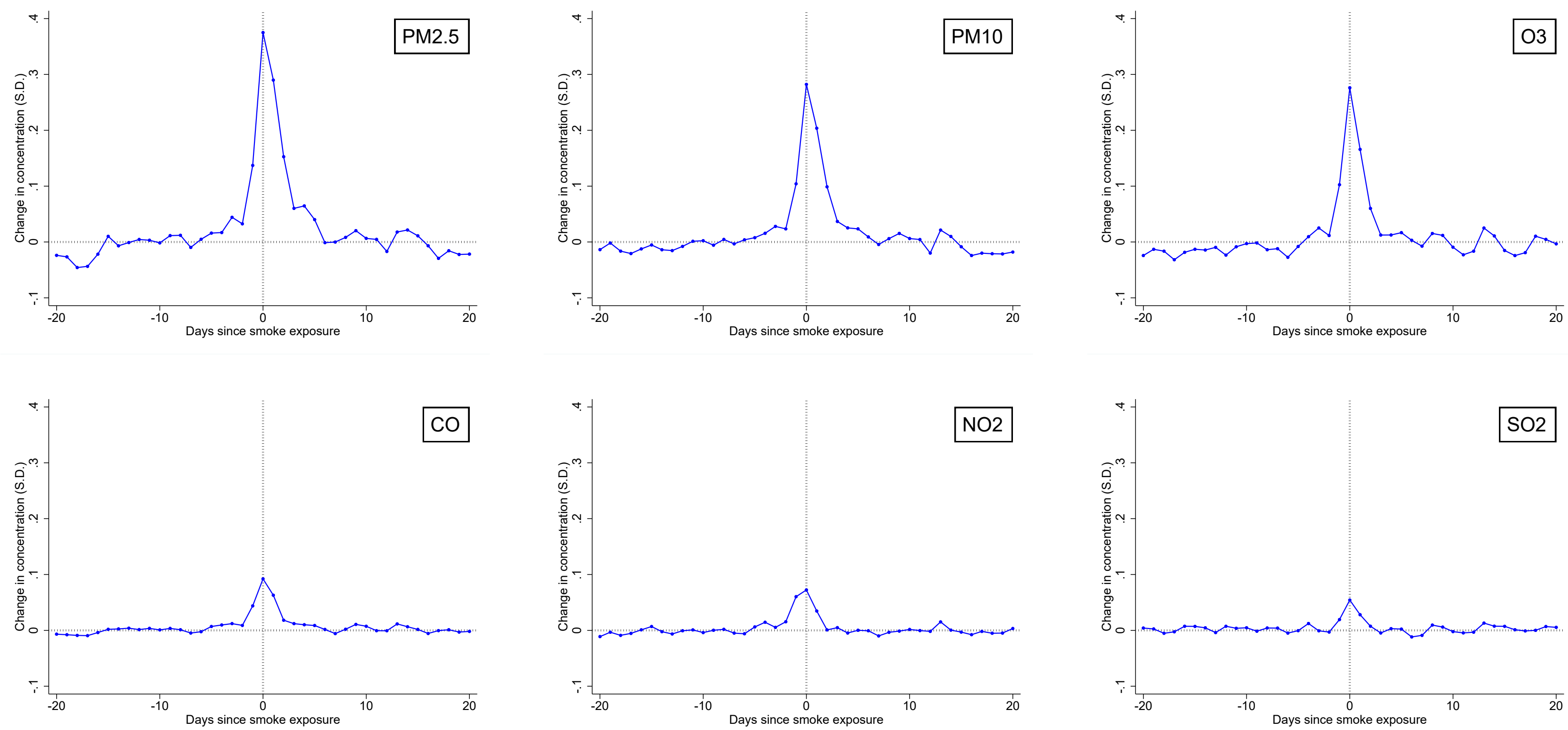
Notes: This map depicts smoke patterns on May 7, 2016, at 9:20 a.m. The Fort McMurray fires in Northern Canada can be seen north of Alberta. This large wildfire produces a smoke plume that reaches the upper Midwest of the United States. Wildfires in the U.S. Southeast produce plumes reaching Canada.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

Figure A.2: Wildfire Smoke and Ground-level $PM_{2.5}$: 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-degree angle bins of daily wind direction, 60-degree angle bins of daily wind direction fully interacted with state dummies, and 60-degree angle bins of daily wind direction fully interacted with county dummies. The regression incorporates 41 smoke indicators and controls for county-by-day-of-year fixed effects and state-by-year fixed effects.

Figure A.3: Wildfire Smoke Shock to Ground-level Pollution



Notes: Each panel shows coefficients from a regression of daily standardized (mean of zero, standard deviation of one) pollutant concentration on indicators of daily smoke exposure up to 20 days before and after the day of observation. The regression incorporates 41 smoke indicators and controls for county-by-day-of-year fixed effects and state-by-year fixed effects.

Table A.1: Robustness Checks: Reduced-Form Regressions

	(1) $PM_{2.5}$	(2) earnings	(3) employment	(4) lfp
A. Smoke measurement				
∑ %county smoked	0.053***	-4.102***	-75.0***	-25.3***
	(0.006)	(0.779)	(20.0)	(9.6)
B. Weather controls				
Temp. Ppt. Wdir. Wspd.	0.043***	-4.950***	-76.3***	-32.8***
	(0.006)	(0.791)	(18.9)	(9.6)
Wdir. × state	0.048***	-5.019***	-59.6***	-32.0***
	(0.006)	(0.793)	(19.0)	(9.3)
Wdir. × county	0.048***	-5.312***	-63.1***	-32.0***
	(0.007)	(0.864)	(20.3)	(9.9)
C. Fixed effects controls				
state-by-year FEs (baseline)	0.056***	-5.217***	-79.6***	-38.7***
	(0.007)	(0.776)	(21.9)	(9.2)
division-by-year FEs	0.053***	-5.399***	-100.7***	-27.9
	(0.007)	(0.759)	(26.2)	(17.5)
region-by-year FEs	0.054***	-5.212***	-109.2***	-26.0
	(0.007)	(0.773)	(29.6)	(20.5)
year FEs	0.057***	-4.421***	-132.9***	13.5
	(0.008)	(0.797)	(33.2)	(22.3)
D. Annual data				
state-by-year FEs	0.036***	1.083	-3.5	-30.2
	(0.005)	(4.252)	(37.1)	(25.0)
division-by-year FEs	0.016***	-5.902***	-80.0***	15.8
	(0.004)	(2.075)	(26.1)	(16.9)
region-by-year FEs	0.017***	-4.139***	-79.1***	11.2
	(0.003)	(1.454)	(21.8)	(13.7)
year FEs	0.019***	0.045	-82.8***	51.2***
	(0.003)	(1.377)	(18.3)	(10.4)
E. Outcome specification				
Lvl spec. w/ trends	0.060***	-2.454***	-42.7***	-24.7***
	(0.006)	(0.596)	(11.1)	(7.4)
Lvl spec. wo/ trends	0.056***	-1.581	10.8	-25.3***
	(0.007)	(0.965)	(8.6)	(2.1)
First-diff spec	0.063***	-3.663***	-51.6***	-26.9***
	(0.006)	(0.654)	(16.1)	(9.0)
F. Standard errors clustering				
	0.056	-5.217	-79.6	-38.7
County + division-by-quarter	(0.009)***	(1.062)***	(37.7)**	(13.1)***
County + region-by-quarter	(0.011)***	(1.432)***	(51.9)	(16.4)**
County + quarter	(0.011)***	(2.077)**	(81.6)	(26.6)
County	(0.004)***	(0.470)***	(10.0)***	(5.7)***
State	(0.013)***	(0.949)***	(23.0)**	(9.5)***

Notes: Each cell is a separate regression. Row names indicate the type of robustness checks performed. All regressions are weighted by county population (columns 1, 2, and 4) and population aged over 16 (column 3), and include county-by-quarter-of-year fixed effects and state-by-year fixed effects. Unless otherwise noted, standard errors are two-way clustered at the county and state-by-quarter levels. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.2: Robustness Checks: IV Regressions

		(1)	(2)	(3)
		earnings	employment	lfp
A. Smoke measurement				
∑ %county smoked	F=89.9	-83.409***	-1738.9***	-506.3**
		(19.517)	(394.1)	(205.1)
B. Weather controls				
Temp. Ppt. Wdir. Wspd.	F=45.9	-124.074***	-2065.7***	-814.8***
		(28.967)	(544.2)	(231.5)
Wdirx × state	F=56.0	-113.794***	-1643.9***	-758.3***
		(25.824)	(453.2)	(199.7)
Wdirx × county	F=50.0	-123.416***	-1768.0***	-778.0***
		(29.247)	(513.3)	(226.9)
B. Fixed effects controls				
state-by-year FEs (baseline)	F=71.8	-103.1***	-1750.1***	-790.9***
		(20.4)	(434.8)	(182.1)
division-by-year FEs	F=62.5	-110.3***	-2183.7***	-637.7*
		(21.8)	(561.8)	(348.9)
region-by-year FEs	F=61.7	-105.040***	-2191.8***	-715.3*
		(20.492)	(596.1)	(400.9)
year FEs	F=47.8	-85.368***	-2607.6***	-25.7
		(19.977)	(710.0)	(418.9)
C. Annual data				
state-by-year FEs	F=50.2	41.562	-99.6	-658.9
		(144.336)	(1172.0)	(753.6)
division-by-year FEs	F=20.1	-357.457*	-4851.0**	1048.7
		(185.348)	(2350.1)	(1233.9)
region-by-year FEs	F=25.7	-219.809*	-3929.2**	-171.9
		(115.260)	(1849.6)	(935.4)
year FEs	F=42.1	14.799	-4585.5***	2093.1***
		(89.288)	(1479.2)	(769.0)
D. Outcome specification				
Lvl spec. w/ trends	F=115.8	-43.572***	-848.0***	-492.6***
		(12.989)	(201.0)	(157.3)
Lvl spec. wo/ trends	F=71.9	-27.721	206.9***	-451.9***
		(22.200)	(68.8)	(73.1)
First-diff spec.	F=97.9	-65.9***	-1069.6***	-462.8***
		(14.8)	(291.5)	(153.3)
E. Standard errors clustering				
		-103.077	-1750.1	-790.9
County + division-by-quarter	F=35.9	(27.610)***	(761.5)**	(262.9)***
County + region-by-quarter	F=26.3	(34.802)***	(1012.3)*	(333.9)**
County + quarter	F=25.0	(43.372)**	(1579.7)	(511.1)
County	F=190.5	(13.611)***	(233.4)***	(123.9)***
State	F=18.2	(39.845)**	(503.0)***	(285.1)***

Notes: Each cell is a separate 2SLS regression. Row names indicate the type of robustness checks performed. All regressions are weighted by county population (columns 1, 2, and 4) and population aged over 16 (column 3), and include county-by-quarter-of-year fixed effects and state-by-year fixed effects. Unless otherwise noted, standard errors are two-way clustered at the county and state-by-quarter levels. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.3: Air Pollution and Earnings: OLS Regressions with Multiple Pollutants

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

Notes: Each column is a separate regression. Pollutants are measured in $\mu g/m^3$ ($PM_{2.5}$ and PM_{10}), ppb (O_3), and ppm (SO_2 and NO_2). All regressions are weighted by county population, and include county-by-quarter-of-year fixed effects and state-by-year fixed effects. Standard errors are two-way clustered at the county and state-by-quarter levels. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.4: Population Flow Responses

	(1)	(2)	(3)
	in-migration (log)	out-migration (log)	tax-exemptions (log)
Smoke	-0.003	0.0001	-0.010
	(0.015)	(0.012)	(0.007)
Observations	37,254	37,256	37,284

Notes: The table reports estimated effects of an additional day of wildfire smoke exposure on annual IRS SOI migration outcomes. 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, and state-by-year fixed effects. Standard errors are clustered at both the county and the state-by-year levels.

Table A.5: Sub-industry IV Estimates for the Agricultural Sector

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

Notes: Each cell is a separate regression following the IV estimation equations (5) and (6). The dependent variable is QWI employment for the corresponding sector indicated by the column title. The smoke variable is used as an instrument for county's quarterly average $PM_{2.5}$. All regressions are weighted by county population aged over 16 and include county-by-quarter-of-year fixed effects and state-by-year fixed effects. Standard errors are two-way clustered at the county and state-by-quarter levels. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.6: Wildfire Smoke and Mortality

	(1) all ages	(2) ages 60-	(3) ages 60+
A. Monthly mortality			
Smoke (reduced form)	0.132	0.081*	0.972*
	(0.110)	(0.043)	(0.522)
$PM_{2.5}$ (OLS)	0.480***	0.148**	1.273
	(0.167)	(0.061)	(0.820)
$\hat{PM}_{2.5}$ (IV)	0.379	0.270	4.446
	(0.648)	(0.259)	(3.335)
	[F=103.5]	[F=104.2]	[F=97.9]
B. Quarterly mortality			
Smoke (reduced form)	-0.118	0.045	1.162
	(0.186)	(0.049)	(0.934)
$PM_{2.5}$ (OLS)	0.628	0.247	-2.131
	(1.032)	(0.310)	(4.997)
$\hat{PM}_{2.5}$ (IV)	-5.908	1.468	-8.889
	(5.415)	(1.480)	(28.206)
	[F=42.6]	[F=43.3]	[F=39.1]
Mean monthly mortality	678.762	168.445	2845.111
Mean quarterly mortality	2033.419	506.850	8600.272
Observations (monthly)	330,442	330,442	330,442
Observations (quarterly)	123,422	123,422	123,422

Notes: Each cell represents a separate regression. Outcome variables are all-age mortality (column 1), mortality among age below 60 (column 2), and mortality among age above 60 (column 3). "Smoke" counts the number of days a county is fully covered by wildfire smoke plumes. In IV estimation, the smoke variable is used as an instrument for county's quarterly average $PM_{2.5}$. All regressions are weighted by county population in the relevant age groups, and include county×month-of-year fixed effects and census state×year fixed effects. Standard errors are two-way clustered at the county and state-by-month levels (panel A) and county and state-by-quarter levels (panel B). *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.