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

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**PRELIMINARY AND INCOMPLETE**
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**Abstract**

This paper examines the effect of wildfire smoke on labor markets. Wildfire smoke travels hundreds and even thousands of miles from its source, generating plausibly exogenous air pollution events in distant cities. Using annual income data, we find that workers experience earnings losses of 10% of one day's income per day of smoke exposure. The effects at the national level aggregate to 0.3% of annual labor income, nearly 10 times expenditures on fire prevention and suppression. We find modest non-linearities, and the largest responses in well-off areas, measured by income or unemployment rates. As well, we document extensive margin and retirement responses, a novel channel in the literature. Although they affect a small share of people, extensive margin effects appear to explain a large share of the income response to air pollution events. We examine the implications for wildfire policy.

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Air pollution has been shown to reduce hours worked and decrease both outdoor and indoor worker productivity.[1] As well, air pollution may dampen demand for goods and services, such as entertainment, hospitality and tourism.[2] However, existing studies focus on specific causal pathways and narrow settings, largely to address concerns about the confounding of pollution's effects on labor markets with the direct effect of economic activity. As a consequence, far less is known about the overall magnitudes and population-level effects of air pollution on labor markets.

In this paper, we extend the literature on the effects of air pollution on labor markets to the study of wildfire. Unlike variation used in previous studies on the effects of air pollution on labor markets, wildfire provides a plausibly exogenous source of air pollution events that are widespread and geographically dispersed, so much so that wildfire is an important policy issue in its own right. Wildfire burns a large and rising amount of land in the United States—an average of 6 million acres per year since the year 2000 and over 10 million acres in 2015, the worst fire season in 50 years—and the National Research Council estimates that each degree increase in temperature may lead to a quadrupling of acreage burned.[3] Driven by shifting wind currents, wildfire smoke plumes can travel hundreds of miles, affecting cities at great distances from the fire itself. Most of the resulting smoke events are modest in size: the average effects on daily measures of the Environmental Protection Agency's criteria pollutants range from one-third of a standard deviation in particulate matter smaller than 2.5 microns ($PM_{2.5}$), one-quarter of a standard deviation in particulate matter smaller than 10 microns ($PM_{10}$) and ozone ($O_3$), to less than a tenth of a standard deviation in carbon monoxide (CO), nitrous oxide ($NO_2$) and sulfer dioxide ($SO_2$).[4] Thus, the range of variation in air quality, and composition of wildfire smoke make wildfire smoke exposure a relevant natural experiment for environmental policy in the United States. Additionally, satellite images provided by the National Oceanic and Atmospheric Administration can be used to

[1] See Hanna and Oliva (2015) for effects on hours worked, Graff Zivin and Neidell (2012) for the productivity of agricultural workers, Chang et al. (2014) for the productivity of indoor pear packers, Li et al. (2015) for the productivity of Chinese manufacturers, Adhvaryu et al. (2016) for the productivity of Indian manufacturers, Chang et al. (2016) for the productivity of indoor call center workers, Lichter et al. (2015) for productivity of soccer players, and Archsmith (2015) for the decision-making of baseball umpires.

[2] See Graff Zivin and Neidell (2009) and Aldy and Bind (2014) on effects on demand for goods and services.

[3] The National Interagency Fire Center (NIFC) keep records of wildfires and acreage burned. Climate change is projected to increase temperatures and reduce precipitation, leading to longer and more intense fire seasons; see National Research Council (2011) for more details.

[4] These exposures are modest compared to daily variation in air quality, but if experienced for an entire year, they would reflect an increase of 3 standard deviation in $PM_{2.5}$ and a 1.5 standard deviation increase in $PM_{10}$ and $O_3$ (ozone). Recent EPA rules emphasize particulate matter and ozone, the primary components of wildfire smoke plumes.

track these smoke plumes at high frequencies and very fine geographic levels.

We find that wildfire smoke is associated with a reduction in labor market earnings that is far larger than the direct costs of fire-related damage or the existing measures of health costs. In contrast to much of the previous literature, the majority of the outcome data is at the quarterly or annual-level, allowing us to measure the combined short-run and medium-to-long-run, impacts of these shocks. Using annual, ZIP code-level data from the Internal Revenue Service we find wildfire smoke exposure generates significant declines in annual income. An additional day of exposure to wildfire smoke lowers the average annual income in a ZIP code by 10% of daily income. When we exclude ZIP codes affected by fire, where firefighting and rebuilding may temporarily increase incomes, the estimated effect rises to 12%. As the satellite can detect wildfire smoke exposure on over 6% of people-days, these effects are important for the determination of national labor income. In our back-of-the-envelope calculations assuming marginal responses can be applied to all smoke days, the total effect of wildfire on labor income is over $35 billion annually. By comparison, federal expenditures on wildfire suppression and prevention were less than $4 billion in 2015, one of the worst fire years on record.

We also find several non-linear relationships between income and both the intensity of smoke exposure and the total number of smoke exposure days over the year. We measure intensity by restricting the coding of smoke exposure days to those ZIP codes that are entirely surrounded by other exposed ZIP codes. As might be expected, areas on the interior of the plumes show both larger responses in criteria pollutant concentrations and income losses, approaching 20% per exposure day. As most of the US lacks pollution monitor data, we cannot measure the exact pollution-income gradient. However, when we examine outcomes in ZIP codes near pollution monitors, we find an increasing within-day effect relative to an index of air pollution. In contrast, the effect of additional pollution days appears to decline with previous smoke exposure days.

We next turn to the exploration of a novel mechanism in the literature on air pollution and labor markets, extensive margin labor supply and retirement. It is well-known that the young and old are most vulnerable to pollution; however, most studies of the effect of air quality on the elderly have focused on health, and mortality, in particular.[5] Medical and public health studies find that vulnerability to respiratory and circulatory illness rises with age, suggesting the productivity and labor supply of older workers may be particularly responsive

[5]For examples of the mortality literature, see Dockery et al. (1993) and Pope et al. (2009). A recent paper on air pollution and health, Schlenker and Walker (2016), documents age-related responses, including the largest effects for the elderly; however, important responses are found among the non-elderly, as well.

to air pollution.(Bentayeb et al. (2012)) For older workers, frictional labor markets and the availability of retirement benefits may multiply the effect of short-run shocks to health and productivity, as the costs of job loss or transitions between jobs may be much larger for them than for younger workers.[6] Using data from the Social Security Administration, and county-level data from the American Community Survey, we test the hypothesis of a larger effect on older workers. We find two pieces of support. First, we document extensive margin responses in the American Community Survey: each day of smoke exposure reduces labor force participation by 0.0096 percentage points. Although this is a small effect, with an average of 22 smoke exposure days per year, the total effect is a decrease in LFP of 0.21 percentage points at an annual basis. Back of the envelope calculations suggest this extensive margin effect may explain as much as half of the overall decrease in income. Second, consistent with a larger effect for older workers, we find increases in both Social Security retirement beneficiaries and income in exposed areas.

We further explore heterogeneity in the effects to shed light on additional mechanisms that may explain the decline in labor market earnings. First, we examine the interaction of smoke plumes with local economic conditions. The estimated effects are much larger in tighter labor markets, declining to almost zero in those areas hit hardest during the Great Recession. This evidence is consistent with the view that earnings declines represent a behavioral response to the smoke—avoidance behaviror—rather than the imposition of a constraint, as would be the case if people were too sick to go to work. Effects are largest in urban and above-average income areas, consistent with an avoidance behavior story. Second, we estimate heterogeneous effects by industry, finding suggestive evidence of short-run labor demand effects and larger effects in industries with many outdoor occupations. In particular, losses are largest in entertainment, professional services, real estate, utilities, construction and accommodation.[7] Finally, we test for lasting labor demand effects of these shocks by examining unemployment claims in the Quarterly Census of Employment and Wages (QCEW), finding an insignificant coefficient with the wrong sign. Thus, the participation response does not appear to be associated with a labor demand channel working through layoffs.

Our work makes three primary contributions. First, we present quasi-experimental evidence on the magnitudes of responses and incidence of air pollution events on labor markets at a national level. The rich variation allows us to construct estimates of population-level

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

[7]A caveat on the individual industry results is the statistical significance of most the effects is around $p = 0.1$. However, the overall pattern is suggestive.

responses, examine heterogeneity, and assess the external validity of previous findings in this literature. Our approach is most similar to the empirical strategy in Deschênes and Greenstone (2011), which documents the effect of extreme heat days on annual income measures. These estimates are essential components of almost any cost-benefit analysis or policy evaluation, and in our case, suggest the employment-reducing effects of environmental regulation are at least partially offset by gains to workers along other dimensions. While previous studies have emphasized worker productivity effects (see cites above) and sick-leave (e.g. Hansen and Selte (2000)), it is not clear who bears the incidence of output lost due to these responses. With a nationally-representative study and annual outcomes, we document that labor bears significant income losses in response to transient air pollution events. Put another way, intertemporal substitution does not replace the earnings lost to transient air quality shocks. Regarding the external validity of previous finding, if anything, we find that effects in setting selected for clean natural experiments may understate the overall effects of air pollution events. This may be because our annual and quarterly outcome measures capture both the immediate and medium-run impacts of pollution events.

Second, this paper is the first to document evidence of an effect of air pollution on extensive margin labor supply and retirement outcomes. These labor force participation effects have the potential to explain a large share of variation in income, though they affect a small share of people. It is likely that previous studies have failed to detect such an effect, as very large samples in conjunction with rich geographic variation in pollution events are required in this analysis. In the light of on-going population aging, the importance of a channel from air pollution to retirement is of increasing policy relevance.

Finally, we make the most direct contribution to the wildfire research and policy literatures. While previous research suggests a role for downwind smoke exposure in accounting for the economic impacts of wildfire, this literature has focused almost exclusively on health impacts. As demonstrated in other work in environmental economics, avoidance behavior and costly adaptations often exceed direct costs to health.[8] Our findings demonstrate that downwind exposure is a first-order component in the benefits of wildfire policy, with labor market responses and avoidance behaviors accounting for large changes in income. Neglecting the downwind effects of smoke will lead to a suboptimal allocation of resources to fire management. Besides the overall cost-benefit analysis, there are a number of specific elements of policy that are informed by our findings. On a basic level, wildfire smoke appears to

[8]For more on these costly but indirect responses, see Moretti and Neidell (2011), Barreca et al. (2016) and Deschenes et al. (2012).

be more harmful than previously appreciated, so policy should focus on preventing wildfires from starting and spreading; the narrow goal of defending land and property exposed to fire damage should not be allowed to subsume fire management budgets. Fires generating large smoke plumes that may reach urban centers should be prioritized over fires far from or downwind of population centers. Forest fires consume denser biomass than prairie fires, therefore generate more and thicker smoke, and should be prioritized. Prescribed burning, fires set intentionally to remove fuel, should be set to take into account wind patterns to avoid population exposure. Estimates of the marginal cost of fire fighting and prevention—already sorely lacking in the literature—should consider both the cost of reducing acreage burned, and the cost of reducing smoke. We hope to expand the cost-benefit analysis in future versions of the paper.

# 1 Background on Wildfire Impacts and Policy

*A. Wildfires in the United States and Around the World*

Wildfires represent a growing problem in the United States and around the world. Most wildfires are caused by human activity, however, the conditions that are conducive to the start and spread of wildfires reflect broader forces, such as climate, weather, land use and fire management policy.[9] In the last few decades, a combination of droughts and growing wilderness-urban interface (WUI) has stretched budgets and led to increasing costs and a relative emphasis on fighting rather than preventing fires. Buildup of fuels associated with lower investments in clearing and preventative burning has resulted in increased fire management costs, while also the potential for larger fires and fire-related damage.

While recent fire seasons have broken records for the scale of acres burned and monetary damages, wildfire may grow to be a much larger problem over the coming decades. The long-run driver of increased wildfire is climate change. Hotter, drier climates have led to an increase in the number of fires and length of the fire season across the United States.[10] The National Research Council estimates that each degree increase in temperature could lead to a quadrupling of acreage burnt by wildfire National Research Council (2011). With global temperatures projected to rise by 2-4 degrees over the next 100 years, the importance of fire management policy will grow accordingly.

[9] NIFC estimates an average of 62,000 fires start due to human activity and 10,500 due to lightning each year.

[10] Climate Central (2012) documents trends in wildfire since the 1970s, with references to the wildfire and climate change literature.

Although we focus on the United States in this article, wildfires are a worldwide problem. Countries with large forests, such as Russia, Indonesia and Brazil regularly face threats posed by wildfires. Australia is uniquely exposed to devastating wildfires, due to the hot and dry conditions in the Outback. The economic impacts and policy implications of wildfire differ greatly across regions of world. Outside of the United States and Australia, relatively little research has been done on the impacts of wildfire, with the exception of a number of papers written about the Indonesian fires of 1997.

*B. Previous Research on Air Pollution and the Economic Impacts of Wildfires*

Current research on the damage caused by wildfires largely examines direct costs of the conflagrations, employing a case study approach and focusing on those rare fires which grow to a large size and reach developed areas.[11] Despite significant direct costs from these events, smoke exposure among downwind populations impacts far more people than the fires themselves, and arises even from small and medium-sized fires, and those which pose no direct threat to human settlements. Evidence on these indirect effects of wildfire remains limited, due to both data and methodological challenges.

The potential for important effects of downwind smoke exposure is well-established, even if the magnitude of these effects are uncertain. Research into the economic impacts of wildfires spans a wide range of dimensions. Fires vary greatly in size and intensity, and have numerous direct and indirect impacts that can differ across affected communities. Likely due to the complexity of the threat, there is no uniform means of assessing the costs of wildfires in the United States, and no estimates of total economic costs on an annual (or any other) basis.[12] Here, we breakdown the impacts of wildfires into four categories: losses to forest and environmental resources, losses to buildings and productive land, costs to health, and other impacts, including positive effects on local employment and wages in areas surrounding the fires. To illustrate their magnitudes and variability, we report estimates from specific fires analyzed in the previous literature.

Environmental and forest resources are the most immediate loss to wildfires. Forest fires consumes timber as fuel, a resource which would otherwise be a valuable asset. Butry et al. (2001) estimate $300-500 million losses to Florida's 1998 fires, over half of total losses.

[11] This research documents significant costs to these fires from the destruction of forest and environmental resources, damage to residences and other structures, disruptions to nearby businesses, and the loss of life to firefighters and people living near fire-affected areas. A single large wildfire are estimated to cause over $1 billion dollars in damage to the communities most affected by the fire.

[12] This point is made in Quadrennial Fire Review (2015), Paveglio et al. (2015) and elsewhere.

On the margin, the threat of fire implies that timber should be harvested earlier and at reduced profits, a point which is well understood by resource economists.Another literature has attempted to quantify the lost value in recreational land use due to wildfire.

Direct losses to buildings and productive land have grown to become a primary consideration in fire management due to the growing WUI. Federal estimates of direct losses to homes and buildings in the 1998 Florida fires to be $10-12 million, vastly less than the losses to forest resources. In more recent fires near urban centers, insurance claims have risen to much higher levels. The Valley Fire in California in 2015 destroyed over 2000 structures, including 1300 homes. Insurance claims for the fire exceeded $1 billion by the end of the year, making it the fifth-costliest fire in the history of the state. The insurance company, Aon Benfield, estimated total economic losses from the fire exceeded $2 billion, suggesting the destruction of insured property represented around one-half of losses in the fire. The two most costly fires in California history were the Oakland Hills fire of 1991, causing $2.9 billion in insured costs and the 2007 San Diego fires, which caused $1.8 billion in insured losses.

Health costs are difficult to measure, with a wide range of estimates appearing in the literature (Kochi et al. (2010)). Relatively few lives are lost to wildfire in the United States, for example: the Interagency Fire Center reports 2013 as the worst season in the last decade, with 34 lives lost to wildfire; since 1990, most annual totals are less than 20. However, Kochi et al. (2012) finds significant mortality effects in downwind communities. Valuing mortality effects can be quite difficult, particularly due to harvesting effects (Deschênes and Moretti (2009)). However, increases in mortality suggest health costs due to downwind smoke exposure may be quite significant. Morbidity costs are much more difficult to estimate. A growing biomedical, public health and economics literature clearly demonstrate negative effects of smoke and air pollution exposure on short-run health outcomes. Thelen et al. (2013) documents a clear pattern of increased emergency department (ED) admissions during the 2003 and 2007 San Diego fires; however, the magnitudes of the effects are modest considering the scale of the fire, with ED admissions increasing by around 50% during the fire's peak, and returned to baseline shortly after. Richardson et al. (2012) estimates the economic costs of health effects to be primarily composed of defensive actions and disutility, with only about 10% of costs due to illness. Put another way, willingness to pay (WTP) may far exceed measured health costs.[13]

However, health effects compose only one possible response to air pollution. It is increas-

[13] Heutel et al. (2016) will examine costs in the Medicare population.

ingly recognized that the primary challenge in translating currently available estimates of the effects of smoke and air pollutants to policy-relevant parameters are behavioral responses.[14] These type of responses have the potential be quite important in the case of wildfires. Wildfires receive prominent news coverage, and the smoke plumes contain large particles that form a visible haze in affected areas. Survey research has documented a number of margins of behavioral response to wildfire smoke, such as spending more time indoors, running air conditioners for longer, and missing work (Richardson et al. (2012) and Jones et al. (2015)). Workers and firms may also engage in adaptive behaviors in response to repeated wildfire exposure, for example by constructing buildings sealed from the outside air, installing more and larger air conditioning systems and purchasing air filters.[15] Avoidance and adaptation will mitigate direct the negative effects of exposure, replacing them with more diffuse—but still costly—changes in behavior. The welfare costs of wildfire smoke should properly include the costs of these responses, in addition to those losses which cannot be averted.

Labor market responses to wildfires have generally been thought to impose only small costs or even create benefits. Nielsen-Pincus et al. (2012) finds that large wildfires in the Western United States generate small increases in both employment and wages in the counties and quarters where the fires burn. The most likely explanation is that the stimulative effects of fire suppression and rebuilding offset the costs due to business disruptions during the fires. In the final report on the economic impacts of the October 2007 Southern California wildfires, one of the largest clusters of wildfires in the previous decades, the Employment and Development Department concluded the fires had the potential to cause $500 million in labor market losses due to business disruptions in burnt areas.[16] These losses would far exceed the $130 million spent on fire suppression, but fall short of the $1.9 billion in insured damage to property. As well, disruptions did not result in lasting employment losses: the same report found fire-related unemployment insurance claims in the month after the fire totaled 6427, accounting for 11.5% of UI claims in the affected counties, and less than 2% of the then 533,000 unemployed workers in California.

To summarize, previous research on the economic effects of wildfires has found significant impacts on a number of dimensions. Traditionally, costs estimates have focused on the

[14]See, for example, Chay et al. (2005) for long-run responses and Moretti and Neidell (2011) for shorter-run avoidance behavior.

[15]An emerging literature documents adaptation responses to climate change. See, for example, the literature on the mitigating effects of air conditioning, for example in Barreca et al. (2016), and management responses to air quality in Adhvaryu et al. (2014).

[16]The study considered the totaled quarterly earnings (using the QCEW) within the fire perimeter. No direct assessment of changes in reported earnings was conducted.

destruction of forest resources and buildings as the primary costs of the fires. Direct health costs have usually been modest; however, Richardson et al. (2012) documents significant avoidance behavior that may far exceed direct costs to health. Few studies estimate labor market impacts beyond business disruptions during the fires and the stimulative effects of suppression and rebuilding.

### *C. Wildfire Policy*

In the face of the increasing threat of wildfires, the allocation of resources to fire management and suppression is a subject of considerable and growing controversy. The vast majority of the land burned by wildfire is remote and sparsely populated, where the costs of fighting fires may outweigh the benefits. Allowing fires to burn, besides saving money used to fight them, serves the additional purpose of cleansing forests and prairies of dead and decaying organic material, thereby preventing the accumulation of fuel that may cause larger and more dangerous fires in the future. In practice, fire management resources are increasingly focused on preventing or fighting those few large fires which threaten densely populated areas.[17]

Since at least Sparhawk (1925), the literature on wildfire policy has identified a least-cost-plus-loss rule (equivalent to setting marginal cost equal marginal benefit) for optimal expenditures on fire-management.[18] However, as noted by Butry et al. (2001) and evidenced in the most recent Quadrennial Fire Report, there is no accepted accounting of total costs to wildfire, or generally agreed-upon estimate of the marginal cost of wildfire mitigation.As well, we would argue from the evidence presented in this paper that optimal policy cannot separate the estimation of costs and benefits. For example, if benefits primarily arise from reduced exposure to smoke plumes in distant cities, then prevention rather than suppression may deserve a greater share of resources. In other words, strategic planning considerations in fire management are likely more important for cost-benefit analysis than the calculations for individual, in-progress events.

In the United States, the vast majority of spending on fire management is provided and administered by the federal government.[19] Between FY2002 and FY2012, the federal government averaged $3.33 billion in expenditures on wildfire management, with a small additional share coming from states and local governments. Spending on fire management is divided

[17]The most costly fires documented in previous studies, such as the 1991 Oakland Hills Fire, the 2003 Cedar Fire and the 2007 Witch Fire are those that both grew to enormous size and threatened urban areas.

[18]Gorte and Gorte (1979) discusses the early literature.

[19]Most statistics come from Gorte (2013); see this article for more information.

between preparedness, suppression operations, hazardous fuel reduction, and a number of smaller programs, such as burnt area rehabilitation and research. Preparedness includes recurring expenses for personnel, aviation assets and heavy equipment. Between 2002 and 2012, preparedness composed about a third of expenditures. Suppression costs cover the actual costs of firefighting by federal employees, as well as state, local and private crews. These costs vary with the intensity of the fire season, and compose another third of expenditures. Supplemented with emergency funds, variable costs of fighting fires composes around half of the total budget. The remaining large category of expenditure is fuel reduction. Fuel reduction encompasses preventative measures, such as the removal of biomass and prescribed burning, and composed slightly less than one-fifth of expenditures in FY2002-FY2012.

Over the last few years, a growing share of expenditures has gone to suppression. This reflects both the increase in wildfires due to external forces discussed above, but also the crowding out of funds available for preparedness, hazardous fuel reduction and other programs that may prevent wildfires from starting or growing to threats requiring suppression. The passage of the Federal Land Assistance, Management and Enhancement (FLAME) Act of 2010 was intended to stop this vicious cycle, by making available a dedicated reserve fund for wildfire suppression. However, this fund has experienced rescissions, and as pointed out by Gorte (2013), reduces cost-benefit considerations by breaking the linkage between funding and fire protection activities.

Policy also considers the effects of suppression on future wildfires. One driver in the growth of wildfires is a focus on suppression at the expense of a policy of letting wildfires burn out on their own. Allowing wildfires to burn in areas that do not pose an immediate risk will reduce the biomass available for consumption by future wildfires. Firefighters and other fire management personnel may have incentives to fight all fires, either due to public pressure or income received for fighting those fires. However, a marginal cost-marginal benefit calculation imposes a balance between suppression and allowing some fires to burn. Where that balance lies depends on the costs of wildfires, particularly those far from human settlement.

One of the primary drivers of increasing suppression costs is the growing WUI. The trend towards residences and businesses locating near wilderness areas imposes additional costs on fire management resources. The expanding WUI also distorts fuel reduction priorities, and adds to their costs. Fuel reduction is increasingly focused on WUI areas, reducing funds avaialble for other high-priority areas. As well, fuel reduction usually takes the form of biomass removal and prescribed burning, and in WUI areas these methods require additional public approval processes and safety measures.[20]

A final and important issue for future policy is the question of who should pay for wildfire costs. Current proposals to transfer federal lands to states would shift the burden of wildfire management away from the federal government and onto states.[21] Since states control land use policy (or grant the authroity to lower levels of governemnt to set policy), and land us is a major driver of increased costs of suppression, transfers of federal lands to states could harmonize incentives.[22] However, if wildfires create large negative externalities far from the locations of the fires, responsibility for fire management may be more efficiently managed by the federal authorities.

# 2 Data and Summary Statistics

## 2.1 Data Sources

*A. Wildfire Smoke Plume and Air Pollution Data*

Our first stage data comes from the database constructed in Heutel et al. (2016), which contains daily links between wildfire records, satellite derived measures of wildfire plume dynamics, and ground air pollution and weather monitoring data from year 2006 to 2012. We draw ZIP code-daily observations on wildfire smoke exposure and local air pollution concentration. The ZIP code smoke measure is created by linking individual geo-referenced smoke plume shapefiles provided by the National Oceanic and Atmospheric Administration's (NOAA) Hazard Mapping System (HMS) to ZIP code boundaries using a simple intersection rule. The ambient air pollution monitoring data originated from the Environmental Protection Agency's (EPA) Air Quality System (AQS). For each ZIP code - day and for each pollutant, the average pollution concentration is computed by averaging monitor readings from all pollution monitors that locate within 20 miles to the ZIP code centroid, with monitors that locate closer to the ZIP code centroid receiving a higher weight in computing the average. We draw pollution observations for particulate matters ($PM_{2.5}$ and $PM_{10}$) which are known to be the main pollutants from wildfire smoke. To better understand the full pollution profile of the smoke shock, we also pull observations for ozone ($O_3$), carbon monoxide (CO), sulfur dioxide ($SO_2$), and nitrogen dioxide ($NO_2$). For each ZIP code-day

[20] Hesseln and Berry (2004) estimates prescribed burning costs 43% more and biomass removal 3 times more in WUI areas, due to these factors.

[21] Center for Western Priorities (2014) discusses the potential costs to the states of such a policy.

[22] Holmes et al. (2007) discusses the moral hazard problem in allowing localities to set land use policy.

we also observe if there was any forest fire going on within the ZIP code boundary, according to forest fire records from the National Fire and Aviation Management registers.

A comprehensive assessment of the smoke measure is provided in Heutel et al. (2016). However, we emphasize some features of the data that are highly relevant to this study. First, the raw data for wildfire, smoke plumes, and air pollution are created independently with no contact to each other. This minimizes the concern that the smoke measure may pick up air pollution variations that reflects local economic activities. Second, although the actual drawing of the smoke plume boundaries involves certain degrees of subjectivity by NOAA's smoke analysts, the analyses are mainly based on results from a variety of quality-controlled satellite smoke and fire detection algorithms, and the role of the analysts is to review and modify the results based on their experience (Ruminski, Kondragunta, Draxler, and Zeng, 2006). Heutel et al. (2016) also documents a substantial jump in ZIP code's particulates concentration around the smoke boundary, suggesting that measurement errors due to subjective smoke boundary drawing is minimum at least at the ZIP code level.

### *B. Earnings Data*

Our main earnings data come from ZIP code-level Individual Income Tax Statistics (SOI) from the Internal Revenue Service (IRS). The data is based on stratified probability samples of Individual Income Tax Returns, Form 1040, 1040A, and 1040EZ filed with the IRS.[23][24] For each year, we observe ZIP code level wages and salaries. We also observe the number of personal exemptions which we use to convert wages to per capita level.

The major advantage of the SOI data is that it allows us to observe earnings at a fine geographic level, where we have a high confidence about the accuracy of our smoke measure. However, since SOI data is not based on the universe of tax returns, we also collect public use earnings data from alternative sources that are not subject to sampling errors. The disadvantage of these data sources is that they provide much less geographic detail.

We first collect county-year level payroll data from the Census Bureau's County Business Patterns (CBP). CBP is based on the Census Bureau's Business Register that contains payroll and employment data from administrative records for the universe of single-unit companies and a combination of administrative records and Census data for multi-unit companies. A limitation of CBP data, however, is that it excludes data on self-employed individuals,

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

[24] For example, in 2008, the data is based on more than 328,000 individual forms out of 142 million forms filed.

employees of private households, railroad employees, agricultural production employees, and most government employees.[25]

*C. Retirement and Disability Income Data*

We supplement earnings data with ZIP code-annual level Social Security benefits data from the Social Security Administration (SSA). The data is derived from SSA's Master Beneficiary Record which covers the universe of Social Security beneficiaries who are ever entitled to receive Retirement and Survivors Insurance or Disability Insurance benefits. For each ZIP code-year we observe number of retired, disabled, and widowed beneficiaries, as well as information on total old-age, survivors, and disability insurance benefits amount.

*D. Unemployment and UI Claims Data*

We collect the following demand side measures of labor market outcomes. First, we obtain county-month level employment count from the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages (QCEW) public data files. QCEW contains monthly employment information for a near census of workers covered by State UI laws and Federal workers covered by the Unemployment Compensation for Federal Employees (UCFE) program.[26] For each county and each month, we observe the exact number of covered workers who worked during, or received pay for, the pay period including he 12th of the month. We supplement this dataset with UI claims data collected from the U.S. Department of Labor, which allows us to observe exact number of initial claims for emerging unemployment at the state-week level.

*E. American Community Survey Microdata*

Finally, we obtain demographic and labor market outcomes for more than 8 million individuals from the American Community Survey Integrated Public Use Microdata Series (IPUMS-ACS). The data consists of a 5 year repeated cross sections from year 2007 to 2011 where we observe each individual's age, current and previous year's place of residence, labor force participation status, annual wage and salary income, and social security and disability benefits. The massive size of the dataset allows us to isolate heterogeneous labor market effects for fine subgroups.

[25] <http://www.census.gov/econ/cbp/methodology.htm>

[26] Workers excluded from the QCEW are: members of the armed forces, the self-employed, proprietors, domestic workers, unpaid family workers, and railroad workers covered by the railroad unemployment insurance system.

To measure individual level smoke exposure, we first create daily links between individual wildfire plume shapefiles and the Census Public Use Microdata Areas (PUMAs), the finest geographic unit contained in the public use ACS.[27] On a given day, we define an individual to be exposed to wildfire smoke plume if any proportion of his PUMA of residence is covered by smoke plume on that day. Since geographic location and labor market outcomes of individuals is only observed at the year of the survey, we assume that individual's place of residence does not change within year. We define an individual's PUMA of residence at year $t$ as his reported PUMA of residence at year $t+1$ if he did not migrate in the past year, and for migrants, we assign them back to reported PUMA of residence at year $t$. We then aggregate daily exposure measure to the annual measure $Exposure_t$, and we approximate labor market outcomes using the individual's self report at $t+1$. In other words, we treat every individual as if measurement of demographics and labor market outcomes took place on January 1st each year, and the individual's smoke exposure is measured by the number of days his residence PUMA is covered by smoke from January 1st to December 31st in the previous year. Consequently, our sample goes back to year 2007 since the earliest available smoke measure starts by 2006. Since our identification uses within PUMA variations in smoke exposure across years, we draw ACS sample up to but not include year 2012, when PUMA delineation changed.

We emphasize the following data caveats to our individual level analyses. First, although we assume that demographic characteristics and labor market outcomes are measured at the beginning of each calendar year for coherence in variable definitions, the actual implementation of ACS employs a monthly sampling frame that is not observed in the public use data.[28] Besides, we assume that labor market outcomes is a measure for the past year, whereas work status such as employment and labor market participation are measured for the *week* preceding the survey, which can also create inconsistency in measurement. In the robustness section, we test sensitivity of our results to these assumptions by varying the reference year of our smoke exposure as well as using work status measure that refers to the past year. Second, because PUMAs are defined strictly based on population, sizes of PUMAs vary substantially across the U.S., and therefore our PUMA level smoke exposure measurement may not be as accurate for large PUMAs as for small PUMAs.

[27] PUMAs are spatially contiguous delineation built on Census tracts and counties. The 2000 PUMAs map we use divides the U.S. into more than 2,000 areas with each individual PUMA contains 100,000 to 20,000 people.

[28] <http://www2.census.gov/programs-surveys/acs/methodology/design_and_methodology/acs_design_methodology_ch07_2014.pdf>

# 3 Wildfire Smoke Exposure as a Research Design

In this section, we develop a framework that uses cumulative exogenous smoke shocks to detect aggregate effect of air pollution on labor market outcomes. Researchers who study the labor market effects of environmental hazards face the challenge that labor market outcomes are usually measured at the monthly or even annual level, which makes it difficult to detect significant impact from usually short-living or one time shock to environmental quality. On the other hand, longer run shifts in environmental quality are often policy driven and therefore involve substantial changes in industrial activities, making it hard to cleanly isolate the effect of environmental quality from other economic forces. Recent developments in the literature have provided partial solutions to this difficulty by studying the relationship between air pollution and labor market outcomes in context where it is feasible to observe both pollution and labor market outcomes at high frequency.[29] Although these contributions constitute the important first step in understanding the labor market consequences of air pollution, it remains to be answered to what extent does the established effects in these specific settings generalize to a broader sets of labor markets.

## 3.1 Wildfire Smoke Exposure as Transient Air Pollution Shocks

We emphasize three critical features of the wildfire smoke exposure shocks for our research design. First, driven by shifting wind currents, smoke plumes emitted by wildfires travel hundreds of miles downwind, affecting cities at great distances from the fire itself. Figure 1 presents visual evidence on this fact, where it is clear that spatial patterns of smoke exposure are completely different from wildfires footprints. This effectively minimizes the concern that some labor market outcomes may be affected by direct damages caused by occurrences of wildfires.

Second, smoke shocks give rise to spikes in air pollution concentration with the average magnitude large enough for us to expect significant health and behavioral responses. Table 2 shows that an average smoky day increases $PM_{2.5}$ by more than a third of a standard deviation. The increase in terms of nitrogen dioxide ($NO_2$) concentration is shown to be similar to moving from 30 miles away from a major coal fired power plant to the center of the plant on an average day.

Third, the smoke driven air pollution spikes are very short lived. Figure 2 shows daily

[29] For example, Hanna and Oliva (2015), Adhvaryu et al. (2014), Graff Zivin and Neidell (2012) and Chang et al. (2014)

level pollution event studies for more than 5.4 million ZIP-day smoke events from 2006 to 2012, and from the graph it can be seen that an average smoke driven air pollution surge dissipates in less than 5 days following the shock. The extremely transient nature of the shock makes it less likely to expect any significant labor demand side effect, which is usually hard to rule out when studying policy driven air pollution changes.

### 3.2 Identifying the Effect of Smoke Exposure on Labor Market Outcomes

Our identification exploits variations in annual cumulative smoke exposure days to identify the labor market effects. We first identify more than 5.4 million ZIP code-day smoke exposure events from 2006 to 2012, and aggregate to a ZIP code-annual level exposure measure $Exposure_{zt}$. We then fit the following regression equation:

$$Y_{zt} = \beta \cdot Exposure_{zt} + State_z \times Year_t + \alpha_z + X_{zt}\gamma + \varepsilon_{zt} \tag{1}$$

where $Y_{zt}$ denotes labor market outcomes such as the log of per capita earnings in ZIP code $z$ and year $t$. $\alpha_z$ are ZIP code fixed effects which controls for time invariant differentials in ZIP codes' labor market outcomes. By including state-by-year fixed effects, we effectively identify labor market effects off within-state-and-year, within-ZIP code variation in smoke exposure days, which we assume to be random. The $X_{zt}$ includes time variant weather controls, such as daily temperatures categorized into 12 fine bins, that may independently affect labor market outcomes. To reflect smoke exposure effect on a representative resident, we weight the regressions by ZIP code-annual population estimates. To adjust for both within ZIP code and state-year autocorrelation, we two-way cluster standard errors at the ZIP code and the state-by-year level.

## 4 Labor Market Effects of Smoke Exposure

This section first presents our main results on the reduced form effect of wildfire smoke exposure on labor market outcomes. Since smoke exposure might affect local labor markets in various ways, policy implications can be very different depending upon the exact mechanisms underlying the effect. After presenting our baseline estimates (section 4.1), we then use both aggregate and individual level data to show that the effects are explained by reduced labor force participation and increased Social Security retirement income (section 4.2). We document the effects are strongest in tight labor and housing markets, suggesting avoidance behavior (section 4.3) and provide supportive evidence that the effect is unlikely to be driven exclusively by labor demand change (section 4.4).

## 4.1 Baseline Results

Table 3 presents regression results using the preferred specification and SOI ZIP code earnings as the outcome variable. Our primary income estimates appear in Panel A. Column 1 shows that, on average, an additional day of exposure to wildfire smoke significantly lowers the average annual income in a ZIP code by about 10% of daily income. In column 2, we drop all observations where any forest fire occurred in that ZIP code-year. The results persist with a slight increase in magnitude, suggesting that the result is not driven by ZIP codes that suffer from damage directly caused by wildfires. If anything, the results suggest nearby fires stimulate labor markets, either through wages paid for fire suppression work, or rebuilding.[30] As our interest is in the air pollution effects of the fires, we take the sample that drops fire-ZIP codes as the baseline in the remainder of the analysis. In Column 3, we drop large ZIP codes, where our indicator of smoke exposure may have less power. As expected, the magnitude of the estimates increases further.

We then examine the effect of intensity and duration of exposure using two different strategies. [31] First, to examine the effect of smoke intensity, we examine responses to smoke days that occur in ZIP codes that are entirely surrounded by smoke, which we call "deep exposure." These areas, interior to the plume, should exhibit larger responses to smoke events, and correspondingly larger earnings losses. Second, we examine the marginal effect of additional days of smoke by running regressions with indicators for binned exposure levels.

Panel B of Table 3 reports results for the intensity analysis of deep exposure. Results across the three columns are nearly twice as large in this specification, rising to a 16-20% effect. We interpret this as a validation of the smoke measure, and evidence that more intense smoke is more harmful. However, comparing the increase in the effect size to the size of the change in pollution intensity in Table 2 suggests we do not have the power to recover the marginal damage of increasingly thick smoke. Additionally, as we lack ground monitor data with the same coverage as the satellite measure, we cannot directly perform the two-stage

[30] See Hornbeck and Keniston (2014) for evidence on how fire can stimulate local economic development.

[31] The exact specifications are necessitated by data limitations in direct measurement of the marginal impact of smoke on air pollution. Compared to the satellite measures of smoke, air pollution monitors are neither as geographically dispersed nor operative at the same frequency. Due to both factors, merging the two datasets results in significant loss of precision.

analysis, or examine the exact pollutant concentrations in all exposed zips. We conclude that there is an intensity dimension, and leave the construction of a more precise pollution measure to future work.

We next examine the marginal effect of additional smoke days. Figure 4 displays the effect of binned smoke exposure levels on earnings. The figure combines all days above 60, as the data is sparse and estimates noisy above this threshold; however, the lines are fit to the entire range of the data. The effects display modest evidence of a non-linear pattern. The quadratic term is positive and statistically significant at $p < 0.05$. To put this in perspective, fitting a line to the first 60 days of exposure would result in a slope that is approximately 30% steeper than the slope fit to the entire range of the data. We regard this to be a modest non-linearity, and continue to report average (i.e. linear) effects for most of the remaining analysis.

The marginal effect of smoke exposure aggregates to a important share of national labor income, given the frequency of smoke shocks in the U.S. Table 1 reports that 6% of earnings-weighted zip codes are exposed to smoke. Multiplied by a 10% effect, this is 0.6% of taxable national labor income in the United States, an annual loss of over $50 billion dollars. Even at lower bound of the 95% confidence interval of our estimate, loss of earnings amounts to an alarming $12 billion. In order to translate this to a welfare measure, we would require some knowledge about why earnings are responding; for example, welfare losses are larger if workers receiving lower wages than if they take additional leisure. We discuss welfare effects in Section 5.

We perform several robustness checks in the Appendix. Table A.1 demonstrates robustness to including leads and lags of smoke exposure. In all specifications, the main effect is virtually identical to the baseline specification. Unfortunately, with the length of our panel, we lack the power to find lagged effects. We also test for an effect of exposure on the total number of exemptions claimed in the ZIP code in Table A.2. One concern may be that smoke exposure induces migration, which could bias our estimates. This does not appear to be the case: we find small, insignificant negative coefficients in the main specification, and positive (i.e. wrong-signed) coefficients when we consider the deep exposure measure.

## 4.2 Smoke Exposure, Extensive Margin Effects and Retirement Behavior

The empirical strategy for examining extensive margin and retirement effects follows the same pattern as the main earnings analysis. As discussed in the introduction, we hypothesize that the smoke effects should be strongest among older workers.

We test this hypothesis in the following ways. First, we use individual level data from the American Community Survey (ACS) to test explicitly for labor force participation responses to smoke exposure. Our empirical strategy here mirrors the one used in the referred specification, except that smoke exposure is now defined at the PUMA level, with all regressions controlling flexibly for individual demographics such as age, gender, marital status, and education level. Column 1 of Table 4 reports that a smoky day reduces labor force participation (LFP) by 3.5 percentage points, using the same $Exposure/365$ scaling from the earnings analysis; in raw terms, this is 0.0096 percentage points decrease in LFP for each day of smoke exposure. Evaluated at 22 days of smoke, the average level of exposure, this equates to a 0.21 percentage point decrease in LFP due to wildfire smoke. This effect need not result exclusively from retirement, and based on the health effects estimated in Schlenker and Walker (2016), it is possible that extensive margin effects occur throughout the age distribution. We lack the power to identify the characteristics of those leaving the labor force (such as their pre-retirement earnings), however, back-of-the-envelope calculations suggest the extensive margin effect can explain up to half of the overall earnings effect.

Next, we examine whether wildfire smoke shocks drive up aggregate retirement benefits using ZIP code level data derived from Social Security Administration's administrative records. Table 4 contains results for ZIP code level SSA retirement beneficiaries (Column 2) and per capita retirement benefits (Column 3). We find that an additional smoke exposure day increases the number of retirement beneficiaries by 0.03%, or 11% when scaled to an annual effect. We find a larger increase in per capita retirement benefits of 20% of daily SSA retirement income. The difference in estimates suggests it is wealthier claimants, compared to the average, who are most responsive to these shocks.

## 4.3 The Role of Local Economic Conditions

Since movement of smoke plumes are plausibly independent of changes in local economic conditions, our setting provides a perfect opportunity to investigate the interaction between air pollution shocks and local economic conditions. This analysis can help reveal the mechanisms underlying the observed earnings effect. Specifically, we compare earning response to smoke exposure in place and years when the local economic condition is favorable versus when it is unfavorable. We hypothesize that in the case where earnings effect is driven completely by health effects of pollution, one should expect no significantly differential responses to short term changes in local economic conditions. However, if the reduced earnings are due to costly actions taken to reduce exposure to pollution, then one would expect a less strongly negative earnings effect in unfavorable economic conditions as opposed to favorable ones, as workers substitute between earnings and non-market activities.

We bring two related piece of evidence with more detailed analyses. First, we interact ZIP code-year smoke exposure measure with state-year unemployment rate. Column 1 of Table 5 shows that the magnitude of the earnings effect is very sensitive to state unemployment rate. A 1 point increase in state unemployment rate reduces the magnitudes of the earnings effect by 4.3%. Second, using Zillow's ZIP code home sales price, we interact the smoke exposure measure with "housing market shock", defined as the difference between the ZIP code's annual average median home sale price and its 2005 baseline average. Column 2 shows that, in ZIP codes where sufficient home sales data exists, the negative earnings effect of smoke exposure is stronger in a favorable housing market environment, where a 10% increase in median sales price increases the effect of smoke exposure on earnings by about 0.7%. Not surprisingly, the unemployment rate movements appear to be highly correlated with changes in the price of housing, and we lack the power to separately identify the effects.

We take this evidence as suggestive of avoidance behavior playing an important role in the earnings results. It is well-known that productivity per hour increased during the Great Recession, and it is possible that workers were less likely to respond to poor air quality, or minor health events, as the job market deteriorated. An important caveat is that recessions have been shown to be improve some measures of population health, possibly due to reductions in air pollution from other causes.[32] Although we control for the direct effect of the unemployment rate, we cannot rule out interactions with air pollution and unemployment rates reflect other sources of variation. Taken in conjunction with the larger retirement effects for higher-income claimants, the evidence is consistent with costly avoidance behavior that is more accessible to better-off individuals.

## 4.4 Industry and Labor Demand Effects

Policy implications would be dramatically different if the established earnings effect of smoke exposure comes from employers shifting demand for labor than if it comes from labor supply changes, such as avoidance behavior. Labor demand shocks reflect the imposition of a constraint, through reduced hours or wages, that imply larger welfare costs than supply

[32] While a number of conflicting studies preceded it, evidence for a recession-health link is usually attributed to Ruhm (2000). A variety of mechanisms have been implicated, but broadly, changes in time use appear to be an important channel.

responses. Demand effects may arise directly from reduced spending on tourism, recreation, outdoor leisure activities, hospitality, food away from home, etc. Labor demand effects may also result from shocks to the production technology or productivity of firms.[33] The analysis reveals mixed evidence for labor demand effects; we start with industry responses.

The patterns of industry-specific responses is suggestive of several mechanisms, including labor demand. Using County Business Patterns data on 2-digit industry labor earnings, Figure 6 plots the coefficients from industry-specific regressions. Panel A shows the largest proportional response in the mining, entertainment, professional services, real estate, utilities, construction and accommodation industries. The figure identifies the three industries with effects significant at $p < 0.1$, professional services, real estate and accommodation. Entertainment and accommodation are the two industries most associated with away-from-home leisure activities, and therefore, likely to suffer a decrease in demand for goods and services due to poor air quality; they are jointly significant at $p < 0.1$. Industries that require outdoor work—construction, and agriculture—are not jointly different from zero. (It should be noted that forestry appears in the agriculture sector.) Several industries with flexible hours rank high on the list: professional services, construction, and real estate. The presence of these industries is suggestive of avoidance behavior. Finally, it is worth noting that several industries which have been closely studied in this literature, manufacturing and agriculture, show no sign of decreased incomes. To sum up, the industry-analysis is consistent with an avoidance behavior channel and a role for labor demand shocks in certain sectors.

To further explore the potential role of decreased demand for leisure-goods and services, we separated smoke events occurring on the weekdays and weekends. If the results reflect reduced demand for leisure, then we would expect to see larger results on weekends. Table A.3 finds that responses are indeed larger to weekend smoke days than weekday shocks. However, standard errors grow considerably larger in these specifications, so the weekend result is only significant at a 10% level, and we cannot reject the equality of the weekday and weekend effects. In addition, many other elements of background pollution change over the week, so

[33]One such possibility is through federal air quality regulation that links firm-level pollution abatement costs to local-area air quality. For example, the Clean Air Act in the U.S. specifies that if any particulates pollution monitor within a county exceeds a concentration threshold for more than a single day per year, all polluting sources within that county will have to implement costly pollution abatement technology. Wildfire-driven air pollution spikes are exempted by the Environmental Protection Agency (EPA) from a county's pollution monitoring history; however, the process of removing them from the county's record involves several administrative steps. Localities may take abatement measures preemptively or without an awareness that high pollution readings are attributable to a distant wildfire.

we cannot rule out interactions (chemical or statistical) between, e.g. changes in car exhaust, and the effects of wildfire smoke.

We further test for labor demand effects working through layoffs using county-level QCEW data on employment and UI claims. Specifically, we examine whether smoke exposure prompts decreases in employment or increases in UI claims. The monthly frequency of the data allows us to more flexibly control for seasonal patterns, although the coarse geographic granularity might attenuate our ability to detect meaningful effects. We take advantage of the fact that we are able to observe the *exact* employment and UI claims levels in the data, and provide the following solution reconciling the frequency advantage and the geographic disadvantage of the data. First, using ZIP code-day level smoke exposure data, for each day we count how many individuals within a county or a state is exposed to smoke plume. Next, we aggregate this individual-exposure days measure to the county-month and the state-week level. We then identify the employment effect of smoke exposure using the following equation

$$Employment_{ct} = \beta \cdot PersonDayExposure_{ct} + \alpha_c \times MonthYear_t + Year_t + \varepsilon_{ct} \quad (2)$$

in which $Employment_{ct}$ denotes number of employees in county $c$ at month $t$. $PersonDayExposure_{ct}$ measures the daily number of people that are exposed to wildfire smoke aggregated to the month level. We include county by month-of-year fixed effects to identify employment effect using within county and month-of-year cross year variations in number of smoke days within the month. We further controls for overall year trends using year fixed effects $Year_t$. Standard errors are clustered both at the county level and at the month level. The regression for UI claims effect takes the exact same form, except that the analysis is at state-week level, therefore notation for outcome changes to $Claim_{sw}$ which denotes claims counts in state $s$ and week $w$.

Table A.4 summarizes the results. We find insignificant effect of smoke exposure on either county employment or state UI claims. For example, we find an increase of 1000 worker exposure to smoke increases employment level by 19.6 people and decreases UI claims by 0.15. The coefficient is not statistically significant at the conventional confidence level.

# 5 Social Value of Wildfire Mitigation

Our estimates on the labor market effect of forest fire smoke point to an alternative view of wilderness management. Although protection of local human life and resources are usually considered as the main objectives of wildfire suppression, our research suggests that savings from potential lost wage earnings due to downwind air pollution may far surpass benefits from direct property and natural resource damage prevention. In future work on this project, we hope to formalize the willingness-to-pay calculation. Here we sketch the basics of the contribution of labor market responses to the overall calculation.

We would like to know what portion of the pre-tax earnings response represents welfare loss. If we could quantify the lost welfare represented by the reduced earnings, we would add this to other benefits of wildfire mitigation to measure the marginal damage done by an additional day of smoke exposure. The usual public policy calculation would weigh the marginal willingness to pay for reduced smoke exposure (across all margins of damage, of which the labor market response is only one) against the marginal cost of reducing smoke. Neither margin is estimated in the literature, so it is difficult to translate our results to quantitative policy recommendations of the form "spending on reducing smoke exposure should be some percentage higher."

As a first step, we can make an informal calculation of a lower-bound willingness to pay for the lost earnings with a two conservative assumptions. First, assume the response to smoke comes entirely through the substitution of time between market work and non-market uses, such as home production and leisure, with a net-of-tax labor supply elasticity of unity. Second, assume the affected labor income is taxed at the average tax rate on labor income of 21% (Tax Foundation, 2014). Both of these assumptions are likely to be conservative. With the first assumption, we are ruling out that workers supply the same labor, but receive lower compensation. (Were this to be the case, they would not receive the benefits of leisure or home production that would accrue in a model with labor supply response, and the lost utility would be larger.) As well, a unit elasticity of labor supply is high for the average worker (Saez et al 2012). For the tax rate, the marginal rate on the affected labor income is almost certainly higher than the average tax rate, since marginal tax rates exceed average tax rates at almost every point in the income distribution. The exact calculation would weigh the heterogeneous response across the income distribution by the marginal tax rate at each level; although we lack estimates of the response at different income levels, it is unlikely the response is concentrated among those with low tax rates.

Under these assumptions, lost welfare from the labor market response is 60% of the lost earnings, over $20 billion. The lost tax income is pure deadweight loss, as workers do not consider the externality on the tax system. Of the remaining 80%, a simple consumer surplus calculation with a unit elasticity implies that half of the response is compensated by other sources of income.

## 6 Conclusion

We estimate the causal effect of air pollution on labor market outcomes by studying the aggregate impacts of more than 5 million wildfire smoke exposure events driven by shifting wind currents. The local and transient nature of these shocks allows us to isolate the effect of pollution from other economic forces, whereas their repetitiveness and broad geographic coverage enables us to detect their effects on annual wage earnings nationwide. We find that workers experience significant declines in earnings, decreases in labor force participation and increases in retirement income. Results are strongest in zip codes that are completely covered in smoke, and on the first day of smoke events. We document a strong interaction between smoke plume's impact and local economic conditions, where the earnings effect is much stronger in a tight labor market, suggesting the important role of avoidance behavior.

This paper also identifies wildfire as a costly source of air pollution. Although the relative magnitude of the earnings effect cannot be directly compared to other dimensions of annual costs (as these are not yet estimated in the literature), the baseline estimate of $35 billion in lost earnings is far larger than the annual budget of $3-4 billion spent fighting wildfires. Even if this response occur among workers with highly elastic labor supply, the lost tax revenue to these earnings surpasses the annual expenditure on fire management. Thus, the estimates suggest the labor market response to wildfire smoke is a first-order component of the costs of wildfire, a previously unappreciated fact.

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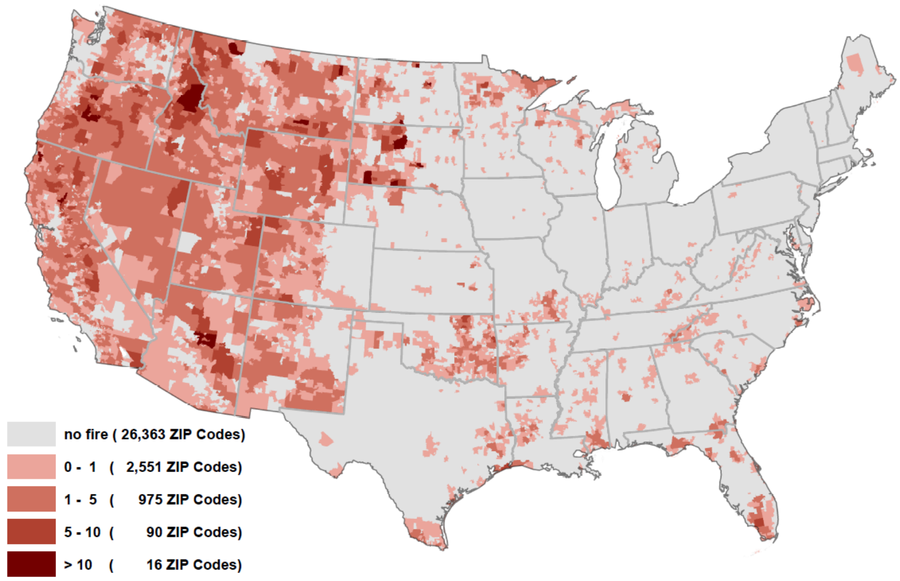
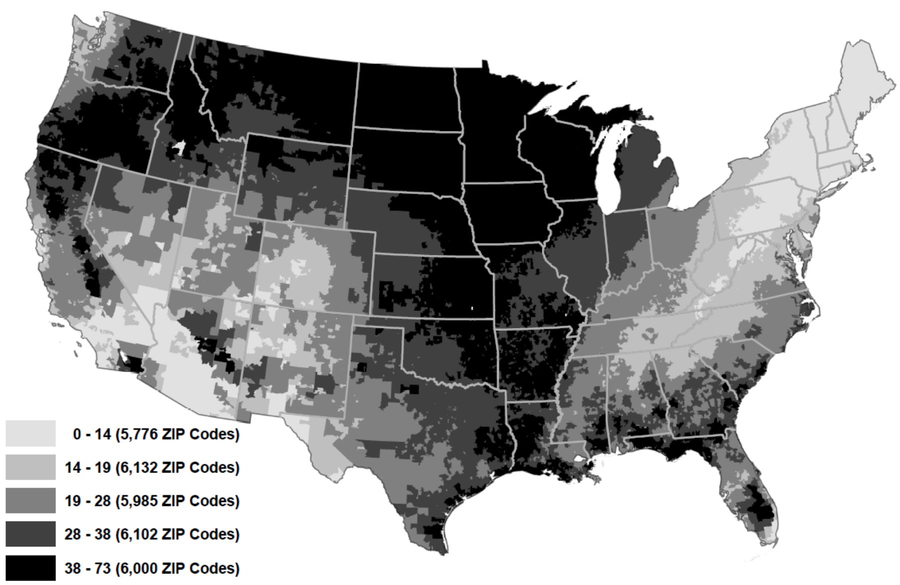
# 7 Figures and Tables

Figure 1: ZIP Code Annual Wildfire and Smoke Exposure 2006-2012

*A. Days of Wildfire*

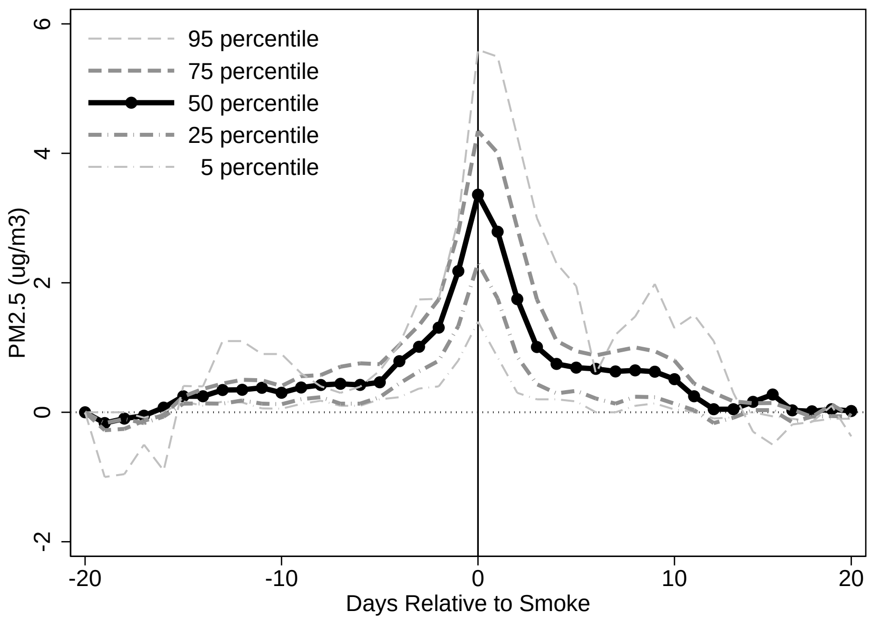



*B. Days of Smoke Exposure*



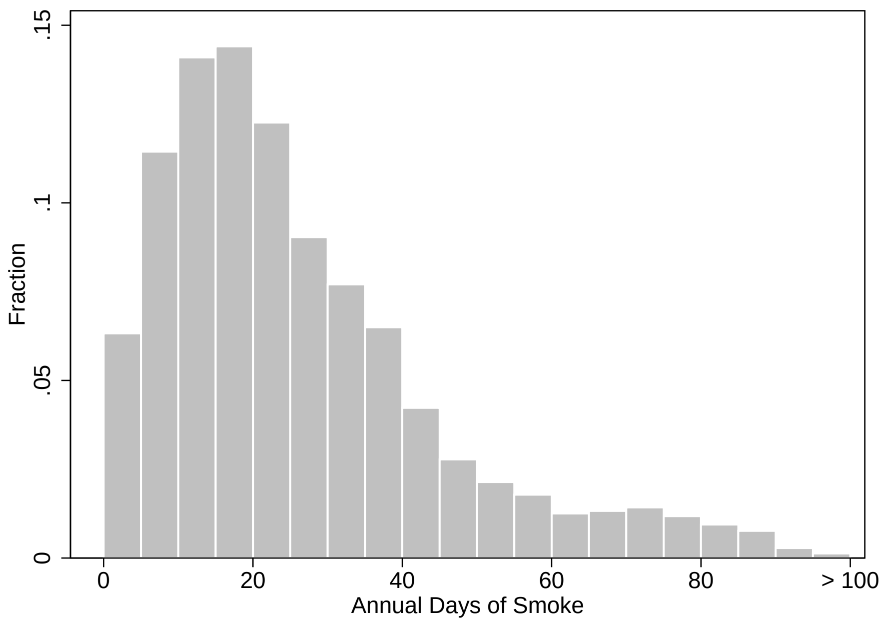

*Notes*: This figure plots ZIP Code level average annual days of wildfire according to the wildfire register data (Panel A) and days of smoke exposure (Panel B) for the lower 48 states. Both wildfire and smoke exposure are calculated over the 2006-2012 period.

Figure 2: Distribution of Intensity of Smoke-Induced Air Pollution Events



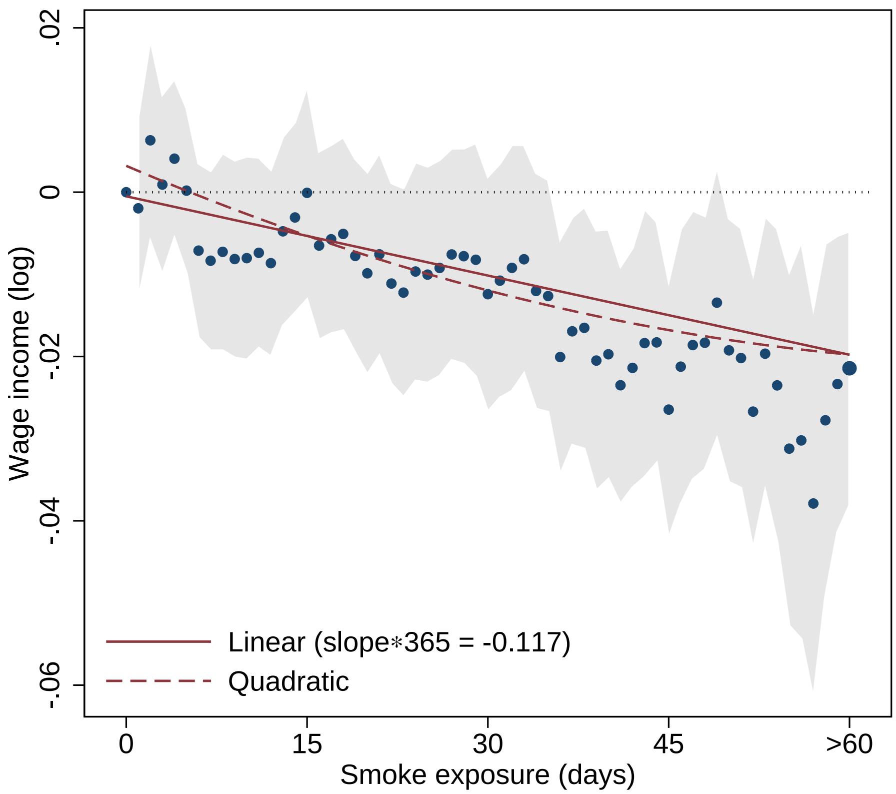

*Notes*: This figure plots the distribution of $PM_{2.5}$ concentration for each day within a 40-day window around 4 million smoke shock events. Event day 0 corresponds to the smoke exposure day, and event day -20 is normalized to 0. Average daily $PM_{2.5}$ concentration is about 11 $\mu g/m^3$.

Figure 3: Distribution of ZIP Code Annual Smoke Exposure Days



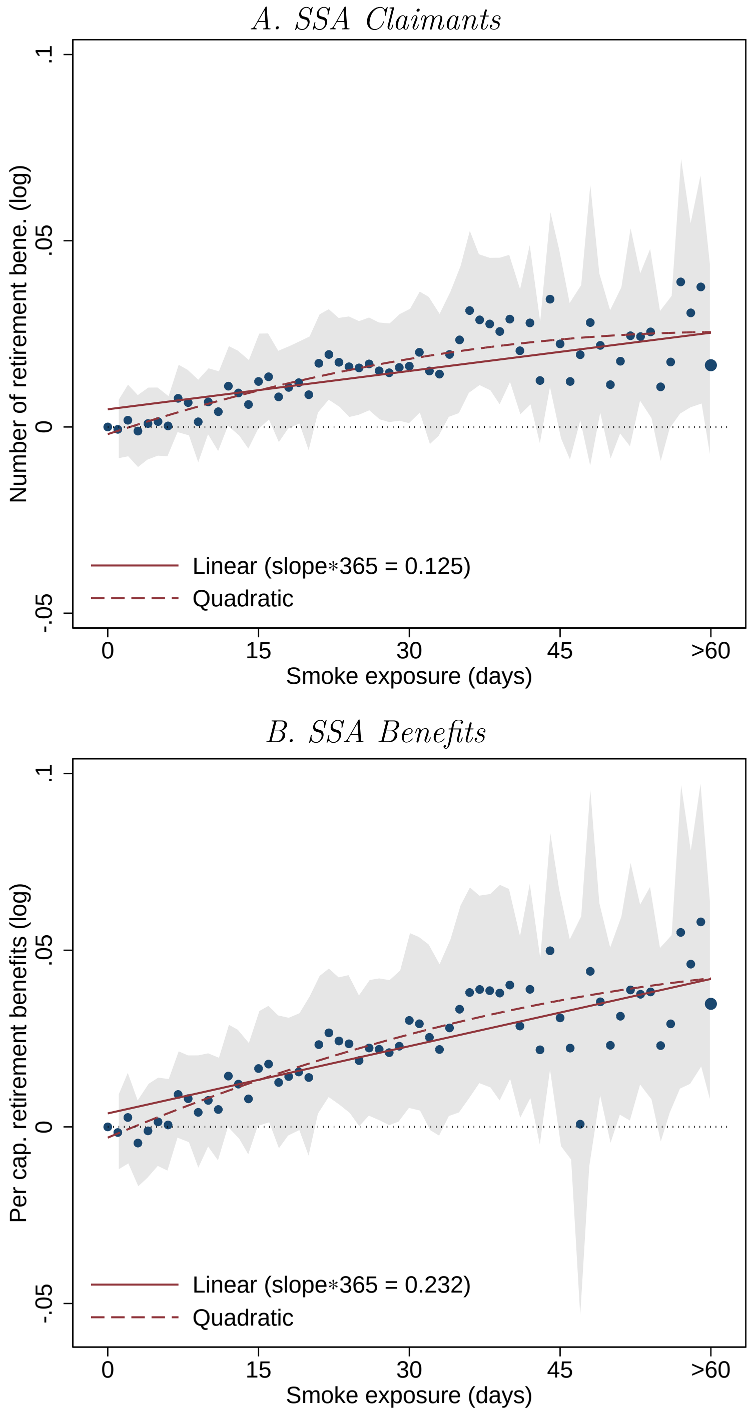

*Notes*: This figure presents the distribution of ZIP Code annual level smoke exposure days. ZIP Codes with more than 100 days of smoke within a year are grouped into the "> 100" category.

Figure 4: Non-linear Effects of Smoke Days on Earnings




*Notes*: The figure presents earnings effects coefficients from a regression with indicators for binned exposure days. Exposure >60 days is collapsed into one bin. Linear and quadratic lines are fit to entire range of data. The quadratic term is 0.00002, and is statistically significant at $p < 0.05$. The shaded regions represent 95% confidence intervals.

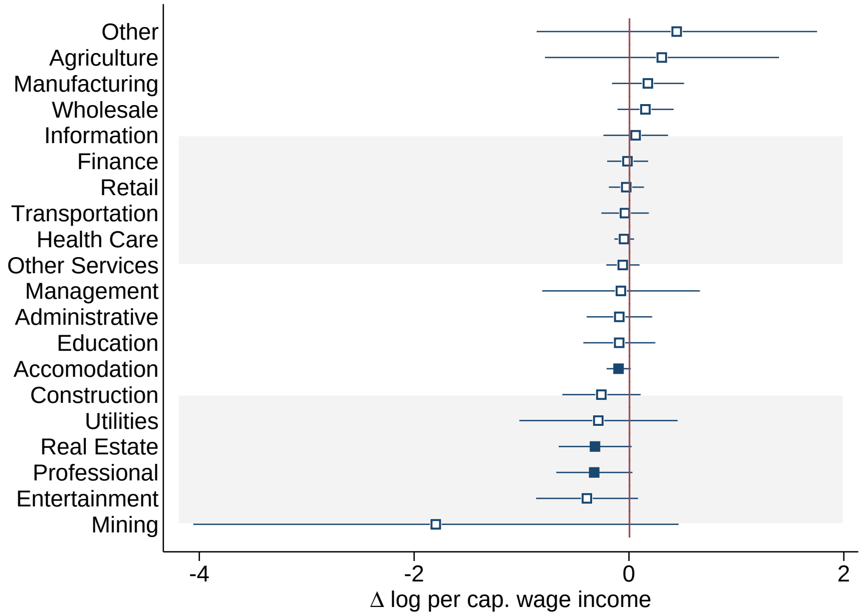
Figure 5: Non-linear Effects of Smoke Days on Social Security Claimants and Benefits



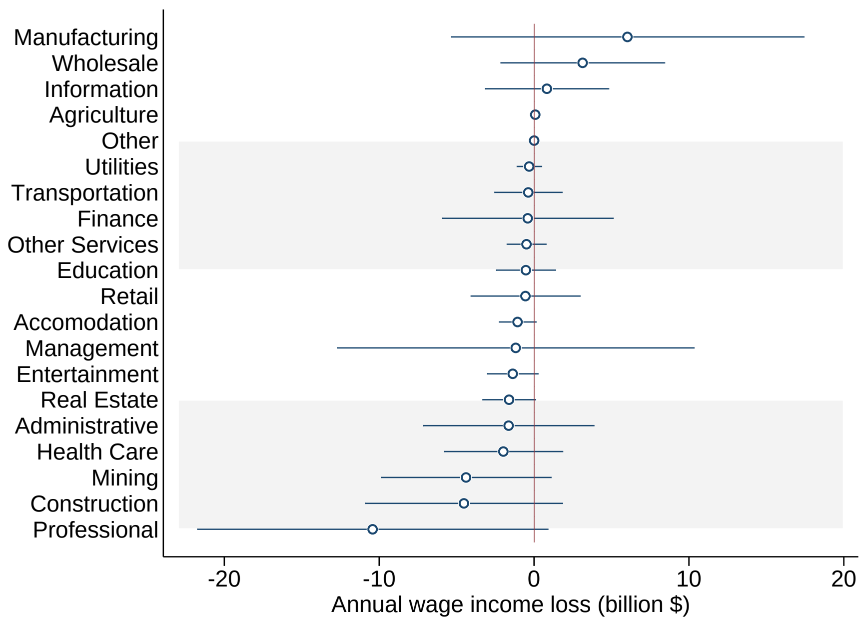

*Notes*: The figure presents coefficients from a regression of log earnings on indicators for binned exposure days. Exposure >60 days is collapsed into one bin. Linear and quadratic lines are fit to entire range of data. Neither quadratic term is statistically significant. The shaded regions represent 95% confidence intervals.

Figure 6: Heterogeneous Effects of Smoke on Industry-specific Labor Earnings

*Panel A. Per Capita Income*




*Panel B. Annual Loss in Income*




*Notes*: Industry-specific effects of smoke on county level payroll income using data from the County Business Patterns. Panel A present coefficients obtained from a single regression where smoke effect is allowed to vary flexibly by 2-digits NAICS. Regression controls for NAICS∗county fixed effects and NAICS∗state∗year fixed effects. Panel B shows industry-specific coefficients scaled up by average annual total industry-wise payroll income during the 2006-2012 period.

Table 1: Summary Statistics of Smoke Exposure

| | All months<br>(1) | June - October<br>(2) |
|---|---|---|
| Distance to the nearest wildfire (miles) | 1442.4 | 1338.3 |
| | (964.6) | (983.4) |
| *N* | 51,376,091 | 27,270,394 |
| Smoke exposure (%) | 6.06 | 11.2 |
| Smoke exposure (days/year) | 22.1 | 17.0 |
| *N* | 69,230,589 | 29,275,250 |

*Notes*: This table shows tax income weighted average ZIP Code daily level distance to the nearest wildfire and smoke exposure frequency. Statistics are calculated separately for all months and for usual wildfire season. Data are from year 2006 to 2012. Reduction in observations in computing distance relative to smoke variables is due to absence of wildfires according to the fire register data.

Table 2: Effects of Smoke Exposure on EPA Criteria Pollutants

| | $PM_{2.5}$ ($\mu g/m^3$) (1) | $PM_{10}$ ($\mu g/m^3$) (2) | $O_3$ (ppb) (3) | CO (ppb) (4) | $NO_2$ (ppm) (5) | $SO_2$ (ppm) (6) |
|---|---|---|---|---|---|---|
| | | | *A. Pollutant Levels* | | | |
| Daily Mean | 10.85 | 22.92 | 2.85 | 41.44 | 12.04 | 2.39 |
| *Exposure* | 3.83 | 7.16 | 0.41 | 2.75 | 1.38 | 0.34 |
| | (0.26) | (0.32) | (0.04) | (0.52) | (0.18) | (0.06) |
| | | | *B. Effect on Daily Mean, Standardized* | | | |
| *Exposure* | 0.34 | 0.24 | 0.25 | 0.07 | 0.10 | 0.07 |
| | (0.02) | (0.02) | (0.02) | (0.01) | (0.01) | (0.01) |
| | | | *C. Effect on Annual Mean, Standardized* | | | |
| *Exposure*/365 | 3.10 | 1.58 | 1.38 | 0.88 | 0.04 | -0.25 |
| | (0.94) | (0.77) | (0.43) | (0.92) | (0.39) | (0.61) |
| Observations | 20.1 mil | 11.4 mil | 29.2 mil | 20.0 mil | 19.1 mil | 21.5 mil |
| # ZIP clusters | 13,541 | 10,401 | 15,069 | 8,942 | 8,587 | 9,726 |
| # Date clusters | 2,496 | 2,496 | 2,496 | 2,496 | 2,496 | 2,496 |

*Notes*: Each cell corresponds to a separate regression. Standardized variables are obtained by subtracting pollutant-specific means and diving by the standard deviation. *Exposure* counts annual number of days a ZIP Code is exposed to wildfire smoke. All regressions include ZIP Code fixed effects and state∗year fixed effects. Weather controls include 9 daily temperature bins and 6 annual precipitation bins. Regressions are weighted by ZIP Code-annual number of tax exemptions. Standard errors are two-way clustered at the ZIP Code and the state-year level.

Table 3: Effect of Wildfire Smoke on Annual Per Capita Wage Income

| Dependent variable: | Per capita wage income (log) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| *A. Independent variable: smoke (days/365)* | | | |
| *Exposure*/365 | -0.100*** | -0.123*** | -0.152*** |
| | (0.038) | (0.043) | (0.043) |
| *B. Independent variable: "deep" smoke (days/365)* | | | |
| *Exposure*/365 | -0.167*** | -0.195*** | -0.193*** |
| | (0.045) | (0.048) | (0.049) |
| Exclude fire ZIP Codes | | ✓ | ✓ |
| Exclude large ZIP Codes | | | ✓ |
| $N$ | 185,719 | 177,482 | 163,973 |
| $N$ (ZIP Codes) | 29,005 | 28,725 | 26,179 |

*Notes*: Each cell corresponds to a separate regression. Dependent variable is log per capita wage income from IRS Statistics of Income. *Exposure* counts number of days a ZIP Code is exposed to wildfire smoke. *Deep Exposure* counts number of days a ZIP Code is exposed to wildfire smoke when all its neighbor ZIP Codes are exposed. Fire ZIP Codes include all ZIP Code-year that ever had wildfires according to the fire register data. All regressions include ZIP Code fixed effects and state∗year fixed effects. Weather controls include 9 daily temperature bins and 6 annual precipitation bins. Regressions are weighted by ZIP Code-annual number of tax exemptions. Standard errors are two-way clustered at the ZIP Code and the state-year level.

Table 4: The Effect of Wildfire Smoke on Labor Force Participation and Retirement Income

| Source of measure: | ACS | Social Security Admin. | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | LFP | Number of retire bene. (log) | Per cap. retire benefits (log) |
| *Exposure*/365 | -0.035** | 0.112** | 0.206*** |
| | (0.016) | (0.054) | (0.065) |
| Mean dep. var. | 0.72 | | |
| $N$ | 8,123,486 | 187,665 | 173,687 |
| $N$ (PUMA) | 2,054 | | |
| $N$ (ZIP Codes) | | 28,410 | 28,373 |

*Notes*: Each column corresponds to a separate regression. Dependent variable is log per capita retirement or disability insurance (DI) income. *Exposure* counts number of days a ZIP Code is exposed to wildfire smoke. Fire ZIP Codes include all ZIP Code-year that ever had wildfires according to the fire register data. All regressions include ZIP Code fixed effects and state∗year fixed effects. Weather controls include 9 daily temperature bins and 6 annual precipitation bins. Regressions are weighted by ZIP Code-annual number of tax exemptions. Standard errors are two-way clustered at the ZIP Code and the state-year level.

Table 5: The Effect of Wildfire Smoke on Log Per Capita Wage Income: Heterogeneity by Local Economic Conditions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *(Exposure)/365* | -0.146*** | -0.129** | -0.152*** | -0.175*** | -0.145** | -0.169** |
| | (0.044) | (0.012) | (0.058) | (0.050) | (0.059) | (0.068) |
| *(Exposure)/365* $*$ *unemployment rate* | 0.038** | | 0.014 | 0.042** | | 0.014 |
| | (0.015) | | (0.020) | (0.017) | | (0.023) |
| *(Exposure)/365* $*$ *home price shock* | | 0.073 | 0.064 | | 0.044 | 0.037 |
| | | (0.122) | (0.130) | | (0.121) | (0.127) |
| Exclude fire ZIP Codes | | | | ✓ | ✓ | ✓ |
| *N* | 185,556 | 50,737 | 50,602 | 177,319 | 49,120 | 48,985 |
| *N* (ZIP Codes) | 28,977 | 8,552 | 8,531 | 28,697 | 8,474 | 8,453 |

*Notes*: Each column corresponds to a separate regression. Dependent variable is log per capita wage income from IRS SOI tax statistics. *Exposure* counts number of days a ZIP Code is exposed to wildfire smoke. *unemployment rate* is demeaned state-year level unemployment rate (%). *home price shock* is ZIP Code-year level demeaned logged change in median home sale price relative to year 2005 average according to Zillow data. Fire ZIP Codes include all ZIP Code-year that ever had wildfires according to the fire register data. All regressions include ZIP Code fixed effects and state$*$year fixed effects. Weather controls include 9 daily temperature bins and 6 annual precipitation bins. Regressions are weighted by ZIP Code-annual number of tax exemptions. Standard errors are two-way clustered at the ZIP Code and the state-year level.

# A Appendix

Table A.1: The Effect of Wildfire Smoke on Log Per Capita Wage Income: Dynamic Specifications

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Exposure* | -0.096*** | -0.082** | -0.093** | -0.116*** | -0.106** | -0.112*** |
| | (0.037) | (0.037) | (0.038) | (0.040) | (0.043) | (0.042) |
| *Exposure* (lag) | -0.061 | | -0.093* | -0.069 | | -0.113** |
| | (0.039) | | (0.049) | (0.046) | | (0.056) |
| *Exposure* (lead) | | -0.042 | -0.060 | | -0.052 | -0.069* |
| | | (0.034) | (0.038) | | (0.039) | (0.041) |
| Exclude fire ZIP Codes | | | | ✓ | ✓ | ✓ |
| *N* | 157,159 | 159,128 | 130,568 | 150,314 | 152,167 | 124,999 |
| *N* (ZIP Codes) | 27,982 | 28,971 | 27,944 | 27,706 | 28,672 | 27,646 |

*Notes*: Each column corresponds to a separate regression. Dependent variable is log per capita wage income from IRS SOI tax statistics. *Exposure* counts number of days a ZIP Code is exposed to wildfire smoke, divided by 365. Fire ZIP Codes include all ZIP Code-year that ever had wildfires according to the fire register data. All regressions include ZIP Code fixed effects and state∗year fixed effects. Weather controls include 9 daily temperature bins and 6 annual precipitation bins. Regressions are weighted by ZIP Code-annual number of tax exemptions. Standard errors are two-way clustered at the ZIP Code and the state-year level.

Table A.2: The Effect of Wildfire Smoke on Log Number of Tax Exemptions

| | (1) | (2) |
|---|---|---|
| *Exposure* | -0.020 | -0.029 |
| | (0.043) | (0.041) |
| *Deep Exposure* | 0.027 | 0.032 |
| | (0.049) | (0.049) |
| Exclude fire ZIP Codes | | ✓ |
| *N* | 185,728 | 177,491 |
| *N* (ZIP Codes) | 29,013 | 28,733 |

*Notes*: Dependent variable is log number of ZIP Code-annual number of tax exemptions from IRS SOI tax statistics. *Exposure* counts number of days a ZIP Code is exposed to wildfire smoke, divided by 365. *Deep Exposure* counts number of days a ZIP Code is exposed to wildfire smoke when all its neighbor ZIP Codes are exposed, divided by 365. Fire ZIP Codes include all ZIP Code-year that ever had wildfires according to the fire register data. All regressions include ZIP Code fixed effects and state∗year fixed effects. Weather controls include 9 daily temperature bins and 6 annual precipitation bins. Regressions are weighted by ZIP Code-annual number of tax exemptions. Standard errors are two-way clustered at the ZIP Code and the state-year level.

Table A.3: The Effect of Wildfire Smoke on Log Per Capita Wage Income: Weekdays vs. Weekend Smoke

| | (1) | (2) |
|---|---|---|
| *Exposure* (weekdays) | -0.054 | -0.070 |
| | (0.065) | (0.071) |
| *Exposure* (weekends) | -0.221 | -0.267* |
| | (0.138) | (0.146) |
| Exclude fire ZIP Codes | | ✓ |
| $N$ | 185,719 | 177,482 |
| $N$ (ZIP Codes) | 29,005 | 28,725 |

*Notes*: Coefficients obtained from a single regression. Dependent variable is log per capita wage income from IRS SOI tax statistics. *Exposure* (weekdays/weekends) is ZIP Code's daily exposure status interacted with dummies that indicate whether the date is a weekday/weekend, aggregated up to the annual level and then divided by 365. Fire ZIP Codes include all ZIP Code-year that ever had wildfires according to the fire register data. All regressions include ZIP Code fixed effects and state∗year fixed effects. Weather controls include 9 daily temperature bins and 6 annual precipitation bins. Regressions are weighted by ZIP Code-annual number of tax exemptions. Standard errors are two-way clustered at the ZIP Code and the state-year level.

Table A.4: Labor Demand Effects of Wildfire Smoke Exposure

| | (1) county employment (level) | (2) state UI claims (level) |
|---|---|---|
| Individual-exposure days | 19.6 | -0.15 |
| | (16.9) | (0.13) |
| Weather Controls | × | × |
| State×year FEs | × | |
| County×month-of-year FEs | × | |
| Year FEs | | × |
| State×week-of-year FEs | | × |
| Observations | 261,156 | 17,836 |
| # County/State clusters | 3,109 | 49 |
| # Month/Week clusters | 84 | 364 |

*Note*: Dependent variable is county-month level employment count for column 1 and state-week level initial UI claims count. "Individual-exposure days" count the daily number of individuals exposed to wildfire smoke aggregated to month or week level. Weather controls include daily average temperature categorized into 12 fine bins. All regressions are weighted by county-year or state-year population estimates. Standard errors are two-way clustered at the county/state and the month/week level.