

Wildfire Smoke, Labour and First Nations Reserves

by

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ABSTRACT

This paper estimates the impact of wildfire smoke on labour supply. The identification strategy relies on a methodology that uses wind speed and direction as instrumental variables. I construct a partial equilibrium model that shows the “substitution effect” and the “income effect” between wildfire smoke and labour supply. My results reveal differences in the direction and magnitude of the two effects between reservation counties and non-reservation counties. Specifically, the “substitution effect” of wildfire smoke on labour supply dominates in most cases. In contrast, the “income effect” is stronger and even outweighs the “substitution effect” for the reservation and the South region. I present an analysis of possible mechanisms for the difference between the two effects. Overall, my findings reveal the importance of labour market channels in air pollution policy responses.

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Chapter 1

Introduction

Severe air pollution has become one of the most problematic environmental issues for countries around the world. According to [World Health Organization \(2022\)](#), almost all the global population (99%) breathe air that exceeds WHO guideline limits and contains high levels of pollutants. The main reasons for this phenomenon include the current increasing demand for energy, the rapid growth in the number of motor vehicles, the dramatic expansion of industry and the increasing prevalence of wildfires. One of the serious consequences of this high level of pollution is that the health of workers is seriously affected. Based on [World Bank \(2022\)](#), the estimated global cost of health damages associated with exposure to air pollution is \$8.1 trillion, equivalent to 6.1 percent of global GDP.

Recent studies in economics have shown that poor air quality can negatively affect several outcomes, including labour supply and productivity ([Graff Zivin and Neidell, 2013](#); [Hanna and Oliva, 2015](#); [Chang et al., 2016](#); [Lichter et al., 2017](#); [Chang et al., 2019](#); [Borgschulte et al., 2022](#)). Research in medicine and psychology also indicates that exposure to air pollution, through its penetration of the body's immune system, is associated with increased mortality, cardiovascular and respiratory diseases, various chronic diseases and even negative mental health outcomes ([Manisalidis et al., 2020](#)). By extension, environmental pollution affects the health level of workers. Consequently, a sudden worsening of air quality may constitute a negative shock that reduces the supply of labour.

Despite its relevance, recent studies on the pollution-labour relationship have been largely focused on analyses of the productivity and working hours in one industry, even though air pollution should have an effect on the larger labour market due to diffusivity, varied with different exposure levels. Consequently, the findings of these papers may not be immediately relevant to other environments with various levels of air pollution, and the influence on work behaviour may be less severe or more severe depending on the presence or absence of adaptation mechanisms to limit exposure.

In this paper, I employ a research design that leverages extensive U.S. labour and wildfire smoke data to evaluate the causal relationship between air pollution and labour force participation. Wildfire-induced air pollution is well suited as an exogenous air pollution shock for avoiding the co-determination of air quality and economic activity. As national oscillations in pollution, wildfires are not caused by factors that directly impact economic activity. Wildfire is also an important type of air pollution to study in the North American context. In recent years, the frequency and severity of wildfires have grown, making them a national pollution source of rising concern. Wildfires account for an average of 20% of PM_{2.5} sources in the U.S., and close to 30% in 2017 ([U.S. Environmental Protection Agency, 2021](#)). The wind may transport smoke from wildfires for thousands of kilometres (as shown in Figure 1), producing plausibly exogenous variation in air pollution events that are geographically distributed, extensive, and unrelated to economic variables such as legislation.

My work also examines the disparate impacts of wildfire smoke exposure for First Nations reservations and non-reservations. Various studies have investigated how colonialism and land dispossession has impacted Indigenous Peoples in recent decades ([Pendakur and Pendakur, 2011](#); [Feir, 2013](#); [Dippel, 2014](#); [Feir et al., 2022](#)). [Farrell et al. \(2021\)](#) found that reservations are more vulnerable to climate change hazards such as wildfire risks. However, as mentioned above, wildfire risk and wildfire smoke risk are not the same. The reservation faces a higher risk of wildfire, but the smoke risk associated with it is not borne solely by Indigenous Peoples. Likewise, they also bear the risk of smoke blowing from other areas. Therefore, while this paper is equally concerned with wildfires, the focus is on wildfire smoke associated with air

pollution, rather than the risk of adjacent wildfires.

To estimate the relationship between air pollution and labour, I compile and merge monthly level data on wildfire-driven PM2.5 ¹ concentrations, labour force participation, and weather controls from January 2016 to December 2019 for all counties in the continental U.S. My final dataset comprises 522,144 observations of monthly labour records across 3,108 counties. The panel form of my data enables me to control for a variety of time-varying omitted variables and depend on within-county comparisons. I include county and state linear time trends controls, as well as a comprehensive set of meteorologic controls, including temperature (maximum and minimum), precipitation and humidity. To account for unobserved time-varying con-founders, I additionally use an instrumental variable method that uses wind speed and direction as sources of exogenous change in local air pollution ([Deryugina et al., 2019](#)).

In this paper, a partial equilibrium model is constructed to explore the effect of wildfire smoke on labour supply. Based on the model results, the paper divides this effect into two effects: the “substitution effect” and the “income effect”. The “substitution effect” represents the negative effect of increased wildfire smoke that leads people to reduce the supply of labour. The “income effect” represents that the increase in wildfire smoke reduces people’s marginal income, making people need to increase their labour supply to obtain the same income. As can be seen from the model in Chapter 3, the “substitution effect” is positive, and the “income effect” can be positive or negative. This uncertainty then increases the complexity of the effect of wildfire smoke on labour supply. When the “substitution effect” and the “income effect” are both positive, the two effects together magnify the impact of wildfire smoke and people significantly reduce the supply of labour. The situation is further complicated when the “income effect” is negative. When the “income effect” exceeds the “substitution effect” in absolute magnitude, it is possible that people increase their labour supply when the smoke is severe instead.

The instrumental variables model in this paper suggests that for every 1 unit increase in

¹In the context of this article, wildfire-driven (wildfire-induced) PM2.5 and wildfire smoke are synonymous. Unless otherwise noted, they will be used interchangeably throughout.

PM2.5 concentration due to wildfire smoke, labour force participation decreases by 0.55%. In general, the “substitution effect” dominates. When I focus only on the reservation, the stronger “income effect” makes the total effect appear insignificant or even significantly positive. This phenomenon is more pronounced for reservations in the South. My results show that for every 1 unit increase in PM2.5 concentration due to wildfire smoke, labour force participation instead increases by 1.2%. My results suggest that for relatively affluent areas, people can adapt to pollution exposure by reducing their labor supply. In poor counties and reservations in the U.S., people may have to continue working to make up for the loss of income due to pollution. This means, in part, that these groups bear a higher cost of wildfire smoke exposure.

In summary, this paper provides an empirical study of the effects of wildfire smoke on labor supply. This paper is related to and contributes to the literature on the effects of air pollution on labor, the varied adaption responses to air pollution, and the disparate impacts between reservation and off-reservation.

The paper is organized as follows. Chapter 2 provides a review of the literature on air pollution and labour issues. In Chapter 3, I construct a partial equilibrium labour supply model under the air pollution. Chapters 4 and 5 describe the data and the empirical methodology, respectively. The main results and the associated robustness checks are reported in Chapter 6. Chapter 7 discusses the potential mechanisms and data limitations. Chapter 8 concludes.

Chapter 2

Literature Review

2.1 Pollution Effects on Health

The U.S. Environmental Protection Agency (EPA) provides information on six important air pollutants: particulate matter (PM), ground-level ozone (O₃), carbon monoxide (CO), sulphur dioxide (SO₂), nitrogen dioxide (NO₂), and lead (Pb). Among them, PM has been the focus of attention in air quality regulations for its penetration, which is closely dependent on its size. PM includes PM₁₀, particles with diameters that are generally 10 micrometers and smaller, and PM_{2.5}, fine particles with diameters that are generally 2.5 micrometers and smaller. PM_{2.5} is of utmost concern due to its ability to remain airborne for extended durations, to readily move from outdoors to inside (making it difficult to prevent exposure), and to lodge deep within the respiratory tract. The majority of human exposure to outdoor PM occurs indoors ([Martins and Da Graca, 2018](#)).

A wealth of epidemiological studies demonstrates how air pollution, especially particulate matter, can dramatically affect human health outcomes, including respiratory disease, immune system disorders, diabetes, cardiovascular disease and psychological disorders ([Brunekreef and Holgate, 2002](#); [Miller et al., 2007](#); [Kampa and Castanas, 2008](#); [Manisalidis et al., 2020](#)). The primary impact of exposure is inflammation in the lungs, which affects the efficiency of the body's exchange of oxygen and carbon dioxide and, as a result, impairs the function of cells

throughout the body. Repeated PM exposure can aggravate early damage and increase chronic inflammation ([Viehmann et al., 2015](#)). Additionally, air pollution affects the cardiovascular system, in part because the inflammatory response begins in the lungs and in part because some kinds of particles may be absorbed directly into blood circulation ([Oberdörster et al., 2004](#)). These alterations brought on by air pollution can influence blood pressure, heart rate variability, blood coagulation, and atherosclerosis ([Giorgini et al., 2016](#)). In turn, these physiological alterations are linked to a prolonged increase in the risk of cardiovascular events such as myocardial infarction, stroke, and heart failure ([Brook et al., 2010](#)). Exposure to pollution may also result in a harm to the brain ([Costa et al., 2019](#)) and a variety of subclinical symptoms such as weariness, poor focus, and memory loss ([Delgado-Saborit et al., 2021](#)).

In short, the emerging evidence on the impacts of pollution on body functioning suggests that pollution can touch almost every aspect of life by impairing cognitive function, altering emotional states, and worsening physical health. As we discuss in Section 2.2, the effects can manifest in domains as wide-ranging as productivity as well as labour supply.

Quantifying the impact of air pollution on human welfare has long been a focus of economists. The earliest studies that directly control for health risks can be traced back to [Dockery et al. \(1993\)](#), which linked the risk of death and air pollution in six U.S. cities, while controlling for individual risk factors. They discovered that the most polluted cities had 26% higher mortality rates than the least polluted, with PM_{2.5} showing the highest correlation. [Pope Iii et al. \(2002\)](#) extended the sample to all metropolitan areas in the U.S. and obtained similar results. The effects on infant mortality have also received attention. [Chay and Greenstone \(2003\)](#) examined the influence of total suspended particulates (TSPs) on infant mortality during the 1981–1982 recession and concluded that a 1% drop in TSPs leads to a 0.35% decline in the infant death rate at the county level. [Currie and Neidell \(2005\)](#) utilized rich individual-level data in California and found that reductions in CO over the 1990s saved nearly one thousand babies in that state. In the setting of developing countries, [Greenstone and Hanna \(2014\)](#) assessed India’s environmental regulations on air and water pollution with a difference-in-differences design. The most effective air regulation led to a slight but statistically insignificant reduction in infant mortal-

ity. Their findings also serve as a reminder that when considering the effects of air pollution, different contexts (for example, developed vs. developing countries) may lead to very different conclusions. There are also patterns of spatial heterogeneity within developed countries ([Chay and Greenstone, 2003](#); [Deryugina et al., 2021](#)). In another developing country plagued by air pollution, the implementation of environmental regulations was shown to have led to a 20% reduction in infant mortality in China ([Tanaka, 2015](#)). In addition, multiple studies, including natural experiments, have demonstrated that increasing air pollution has a considerable impact on infant mortality ([Luechinger, 2014](#); [Cesur et al., 2017](#); [Lee et al., 2018](#); [Anderson, 2020](#); [DeCicca and Malak, 2020](#)) and general mortality ([He et al., 2016](#); [Deryugina et al., 2019](#)).

2.2 Pollution Effects on Labour and Productivity

As mentioned in Section 2.1, pollution exposure can produce, among other symptoms, weariness, irritation, impatience, and loss of concentration. These consequences may have short-term effects on production via labour supply and productivity.

The various physiological effects of pollution can impair job performance in a variety of ways. Perhaps these effects are most apparent in the context of physically taxing labour. [Zivin and Neidell \(2012\)](#) examined daily changes in the daily exposure of piece-rate agricultural labourers to ozone and find that a 10-ppb rise in ozone affects wages by 5.5%, despite the fact that ozone levels are within regulatory limits. They highlighted that the fast start and recovery from ozone exposure imply that the observed productivity reductions are mostly attributable to short-term performance effects and not to deteriorating health. [Chang et al. \(2016\)](#) studied the impact of PM on the productivity of piece-rate pear packers at a facility in Northern California. They showed that a $10 \mu\text{g}/\text{m}^3$ increase in PM_{2.5} affects productivity by around 6 percent, even at levels of pollution substantially below existing federal guidelines. In the setting of developing country, [He et al. \(2019\)](#) studied the effects of PM_{2.5} variation on piece-rate manufacturing worker output in two Chinese cities and failed to find a statistically significant effect of PM_{2.5} during a worker's shift. More recently, [Adhvaryu et al. \(2022\)](#) examined the impact of PM_{2.5}

on garment output, as assessed hourly at several sites in an Indian garment factory. Their estimations suggest a 0.3% decrease in productivity for every $10 \mu\text{g}/\text{m}^3$ rise in PM2.5, with higher impacts for more complicated activities and older employees.

Sports activities, as a special form of physical work, have also attracted a number of researchers to study the effects of air pollution. [Lichter et al. \(2017\)](#) found that higher PM2.5 impairs the performance of professional soccer players in Germany. [Guo and Fu \(2019\)](#) find that marathon runners in China run more slowly on days with higher pollution levels. These studies demonstrate the impacts of pollution on physically fit people, sometimes at quite low concentrations.

All the aforementioned research have focused on physically demanding employment, but pollution may also impair employees' cognitive abilities. [Chang et al. \(2019\)](#) examined the performance of workers in two call centres in China. They found that a 10-unit increase in the air pollution index (API) decreases the number of daily calls by 0.35%. [Archsmith et al. \(2018\)](#) examined the impact of air pollution on Major League Baseball umpires, for whom continuous mental concentration is essential for job performance. CO and PM2.5 were shown to have detrimental effects on the accuracy of calls: a 1 ppm rise in CO decreases the proportion of correct calls by 2%, while a $10 \mu\text{g}/\text{m}^3$ increase in PM2.5 decreases it by 0.4%. [Kahn and Li \(2020\)](#) investigated the influence of PM2.5 on the performance of Chinese trial judges during court proceedings. They discovered that a 1% rise in PM2.5 results in a 0.182% increase in case time (an inverse measure of productivity), with the effects being more pronounced for older judges and more complicated cases. Additionally, they also found that air quality warnings reduce the impacts of pollution, a result consistent with avoidance behaviour.

In addition to effects on worker productivity contingent on employment, there is evidence of substantial labour supply reactions to pollution when considering populations outside the workforce of a single business. [Aragon et al. \(2017\)](#) found consequences of PM2.5 pollution on the labour supply of households in Lima, Peru, especially for households with vulnerable members: A $10 \mu\text{g}/\text{m}^3$ increase in PM2.5 reduces labour by 1.9 hours per week. [Hanna and Oliva \(2015\)](#) found that after the shutdown of a refinery in Mexico City, a 10 ppm decrease in

SO₂ leads to an increase of 1.3 hours per week.

Despite the fact that past research has shown impacts at specific organizations or places, a significant concern is how effectively the conclusions translate to larger scales. [Dechezleprêtre et al. \(2019\)](#) studied economy-wide impacts of pollution using regional and national production and pollution data. They conclude that a 10 µg/m³ increase in PM_{2.5} results in an 8% decrease in production. [Fu et al. \(2021\)](#) examined the impacts of PM_{2.5} on productivity of all significant Chinese companies. According to their estimations, a 10 µg/m³ increase in yearly pollution produces an 8.2% decrease in worker production. These studies indicate that the combined effects of productivity and labour supply have substantial national and even regional consequences. [Borgschulte et al. \(2022\)](#) studied the influence of air pollution on the U.S. employment market by evaluating the effects of drifting wildfire smoke. They discovered that each extra day of exposure to smoke decreases quarterly earnings by roughly 0.1%. In summary, numerous papers have found that air pollution reduces worker productivity and, in some cases, labour supply.

2.3 Pollution Effects on Indigenous Peoples

Despite the fact that air pollution is a worldwide issue, its impacts are unequally distributed, with low-income populations suffering a disproportionate share ([Deryugina et al., 2021](#)). Among those vulnerable populations, Indigenous peoples are of particular concern, given their disparate exposure (see Table 1) and reduced coping capacity. According to Current Population report ([Creamer et al., 2022](#)), although AIAN (American Indian and Alaska Native) people make up only 1.3% of the total U.S. population, they account for 2.6% of the total population living in poverty. In quantitative terms, the poverty rate for AIAN people is 23.2%. This is not only more than twice the national poverty rate (11.6%), but also the highest poverty rate across the six racial/ethnic classifications in the US ¹. In addition, [Farrell et al. \(2021\)](#) compiled a dataset within the modern-day United States and analyzed the long-term effects of land

¹The poverty rates for the other five racial classifications were: White (8.2%); Hispanic (17.2%); Black (19.56%); Asian (9.39%); Two or More Races (14.09%).

dispossession and forced migration on Native North Americans. They discovered that present-day tribal lands are, on average, more vulnerable to climate change risks and hazards, such as higher temperatures and less precipitation. Nearly half of tribes were exposed to an increased risk of wildfires. Second, the present-day tribal lands have diminished economic mineral value, as they are less likely to contain valuable subsurface oil and gas deposits.

There is a lot of literature that focuses on specific types of environmental pollution on Indigenous peoples, the majority of which relates to agriculture, extractive activities and industrial development. The notable sources of pollution include: oil and gas extraction ([Dana et al., 2008](#); [Cepek, 2012](#)), mineral extraction ([Shaw and Welford, 2007](#); [Ashe, 2012](#); [Byrne et al., 2012](#)), toxic waste dumping ([Williams, 1992](#); [Sitkowski, 1994](#); [Brook, 1998](#)), and agro-chemical contamination ([Muir et al., 1992](#)). Also, vegetation burning, an agricultural practice common to some Indigenous groups, may have adverse health effects ([Hanigan et al., 2008](#)). The corresponding health-related issues include cancer risk ([Hurtig and San Sebastián, 2002](#)), mortality ([Watson, 2006](#); [Kunitz et al., 2014](#); [Elder et al., 2016](#); [Gorzig et al., 2022](#)), COVID-19 ([Rodriguez-Lonebear et al., 2020](#)), health care policy ([Kunitz, 2020](#)) and mental health ([Garrett et al., 2015](#); [Akee et al., 2022](#)).

In terms of air pollution, there is some documentation that long-range transport of pollutants is a major problem in the Arctic ([Monitoring et al., 2006](#)). However, there is no literature, according to my search results so far, directly linking air pollution, dominated by PM, to health and welfare outcomes of Indigenous peoples.

2.4 Pollution Effects of Wildfire

Fire is a natural occurrence and an essential part of many ecosystems across the globe, but it also presents a huge threat to human populations. Over the last several decades, wildfires in the United States have expanded in their occurrence and intensity. According to [National Interagency Fire Center \(2022\)](#), the area of wildfires has climbed from a 10-year average of 7.18 million acres to a 5-year average of 7.65 million acres, while suppression costs have increased

from \$2.359 trillion to \$2.863 trillion. These quantified expenses represent just a tiny portion of the societal effect of wildfires. With increasing populations, growing economic activity, and climate change, the threat of wildfires is at an all-time high.

Wildfires affect society and the environment in many ways. During an event, flames pose an urgent danger to people's lives and property ([Milne et al., 2014](#)). Additionally, fire may influence avoidance behaviour ([McCaffrey et al., 2018](#)), ecology ([Pausas and Keeley, 2019](#)), real estate markets ([McCoy and Walsh, 2018](#)), and outdoor enjoyment ([Hesseln et al., 2003](#); [Gellman et al., 2022](#)).

Smoke from wildfires, which contains a large amount of particulate matter, may degrade air quality in the immediate vicinity and hundreds of kilometres away ([O'Dell et al., 2021](#)). [Burke et al. \(2021\)](#) found that wildfires produced around 25% of PM_{2.5} in recent years. A growing literature has begun to document the health impacts of ambient wildfire smoke exposure ([Reid et al., 2016](#); [Cascio, 2018](#); [Xu et al., 2020](#); [Zhou et al., 2021](#)). Specific topics include but are not limited to hospital admission ([Moeltner et al., 2013](#); [Kochi et al., 2016](#)), health care cost ([Johnston et al., 2021](#)), avoidance cost ([Richardson et al., 2013](#); [Jones, 2018](#)), premature death ([Clay et al., 2021](#)), infant mortality ([Jayachandran, 2009](#)), birth weight ([Abdo et al., 2019](#); [Mccoy and Zhao, 2021](#)), preterm birth ([Heft-Neal et al., 2022](#)) and cancer ([Pun et al., 2017](#); [Coleman et al., 2020](#)). In addition, [Holm et al. \(2021\)](#) and [Reid et al. \(2016\)](#) provide an overview of the health effects of wildfire smoke. [Holm et al. \(2021\)](#) is mainly concerned with the effects on children.

The degraded air quality likely resulting from exogenous wildfire smoke makes for an attractive research design to quantify the causal effects of air quality on a variety of health and social consequences. For example, [Borgschulte et al. \(2022\)](#) used the plume data to estimate that wildfire smoke affects U.S. labour market wages by \$93 billion per year, showing the substantial indirect costs connected with wildfires.

Chapter 3

Conceptual Framework

In this paper, I analyze the interaction mechanism between air pollution and labour supply by developing a partial equilibrium model. The reason for constructing a partial equilibrium model, rather than a general equilibrium model, is that air pollution is not a variable that can be determined by the workers themselves. Constructing a general equilibrium model that includes firms would deviate from the focus of this paper. Therefore, I investigate the determination of air quality on labour supply, my primary outcome measure, by constructing a simpler partial equilibrium model. Since this paper focuses on the impact of air pollution on labour supply, some non-focused variables such as saving decisions will be ignored. The individual utility function of the worker is assumed to be:

$$u = u(c, h|\alpha), \quad (3.1)$$

where c is the worker's personal consumption, h is the worker's working hours, and α is the air quality. Since the air quality is beyond the control of the individual, the equation represents the consumption and work time decisions made under certain air quality conditions. If workers cannot tolerate the local air quality, they can move to a place where the air quality is acceptable. Consumption c satisfies the Inada condition (i.e., $u_c > 0$ and $u_{cc} < 0$). According to the assumptions about working hours and worker utility in [Hausman et al. \(1984\)](#), I assume that

labour time is inversely proportional to the utility of the worker¹, i.e., $u_h < 0$ and $u_{hh} < 0$.

I make the following further assumptions about the model. First, the change in air quality is exogenous. In addition, I assume that higher air quality increases the health of workers and their families, giving positive utility to workers, i.e., $u_{h\alpha} > 0$. The effect of air quality on workers' consumption is uncertain: on the one hand, if workers are more willing to go out shopping under better air quality, the utility of workers' consumption is positive ($u_{c\alpha} > 0$); on the other hand, it is possible that better air quality reduces certain consumption such as medicines and fitness ($u_{c\alpha} < 0$). Thus, the expression for the worker's maximized personal utility function is:

$$\max v(h) = \lambda(\alpha) \cdot wh + D(h|\alpha), \quad (3.2)$$

where w is the wage rate and wh is the lifetime labour income of the worker. $\lambda(\alpha)$ denotes the marginal utility of income. I assume that the wage rate is not affected by air pollution. Thus, the first term represents the total utility of lifetime earnings, while the second term $D(h|\alpha)$ represents the negative utility (damage) of working hours for the individual worker under certain air quality conditions. The damage term can be further expressed as:

$$D(h|\alpha) = - \int_0^h u_h(x|\alpha) dx. \quad (3.3)$$

According to Equation 3.3, the assumption $u_{h\alpha} > 0$ can be converted to $D_{h\alpha} < 0$ and the assumption $u_{hh} < 0$ can be converted to $D_{hh} > 0$. The latter inequality represents that the negative marginal utility of working increases as the working hours climb. A worker's individual constraint budget line can be expressed as:

$$wh + y - pc = 0, \quad (3.4)$$

where y denotes the non-labour income of the worker, independent of the air quality. p is the

¹This assumption may be partially inconsistent with reality. For example, when working fewer hours, there may be some positive correlation between worker utility and working hours. Also, a moderate amount of work may bring some satisfaction and social fulfillment.

price of consumption. According to Equations 3.1 to 3.4, I construct the Lagrangian function of individual utility as:

$$\mathcal{L} = u(c, h|\alpha) + \lambda(wh + y - pc). \quad (3.5)$$

Taking derivatives and rearranging yields a decomposition of the effect:

$$\frac{dh}{d\alpha} = \frac{-D_{h\alpha} + \frac{\partial \lambda}{\partial \alpha} w}{D_{hh}}, \quad (3.6)$$

where

$$\frac{\partial \lambda}{\partial \alpha} = \frac{p \cdot u_{c\alpha} \cdot u_{hh} - w \cdot u_{cc} \cdot u_{h\alpha}}{w^2 \cdot u_{cc} + p^2 \cdot u_{hh}}. \quad (3.7)$$

In Equation 3.7, the denominator is negative since $u_{cc} < 0$ and $u_{hh} < 0$. The effect of air quality α on marginal income λ depends mainly on the sign of the numerator. When $u_{c\alpha} \leq 0$ or $0 < u_{c\alpha} < \frac{w \cdot u_{h\alpha} \cdot u_{cc}}{p \cdot u_{hh}}$, the numerator is positive, i.e., $\frac{\partial \lambda}{\partial \alpha} < 0$. In this case, better air quality will reduce the marginal income of workers. When $u_{c\alpha} > \frac{w \cdot u_{h\alpha} \cdot u_{cc}}{p \cdot u_{hh}} > 0$, there is a strong complementarity between consumption and air quality. The negative numerator, i.e., $\frac{\partial \lambda}{\partial \alpha} > 0$, indicates that better air quality will increase the marginal income of workers. The effect of air quality α on working time h can be analyzed by Equation 3.6. Since $D_{h\alpha} < 0$ and $D_{hh} > 0$, the effect depends on the sign of $\frac{\partial \lambda}{\partial \alpha}$, the magnitude and sign of Equation 3.7.

I define the term $-D_{h\alpha}$ in the numerator of Equation 3.6 as the “substitution effect” of air quality on working time. Workers are willing to increase their working hours due to the reduction in negative utility of their work caused by the improved air quality. The term $\frac{\partial \lambda}{\partial \alpha} w$ can be defined as the “income effect” of air quality on working time. As the improvement of air quality may increase the marginal income of workers, they can work fewer hours to get the same income and the supply of labour is reduced. Since there are two possibilities for $\frac{\partial \lambda}{\partial \alpha}$, there are two possibilities for the effect of air quality on working hours accordingly. When $\frac{\partial \lambda}{\partial \alpha} > 0$, the positive “income effect” and the positive “substitution effect” jointly amplify the effect of air quality on labour supply. When $\frac{\partial \lambda}{\partial \alpha} < 0$, the “income effect” is negative, so the effect of air quality on labour supply depends on the magnitudes of the two effects.

In summary, when “income effect” dominates, the supply of labour is likely to increase with worse air pollution. In other cases, the supply of labour decreases as pollution increases. This difference in “income effect” can be related with the level of economic development of different regions ([Rose, 2001](#); [Kimball and Shapiro, 2008](#)). Workers in developed regions may be more concerned about health issues than income levels, so the “substitution effect” is much larger than the “income effect”. For less developed regions, on the other hand, income is critical to sustaining livelihoods. People will choose to work more hours or seek more jobs when air pollution is severe in order to maintain the same total income. This discrepancy also serves as the foundation for the subsequent analysis of heterogeneity. In [Section 6.2](#), I will examine how these two effects vary across geographic dimensions, such as region and reservations.

Chapter 4

Data

4.1 Wildfire Smoke

The daily wildfire smoke PM_{2.5} data were originally developed by [Childs et al. \(2022\)](#). To attribute positive anomalies to smoke, they contrasted satellite-based plume measurements with ground-based Environmental Protection Agency (EPA) monitoring stations observations of smoke PM_{2.5}. Then, they developed a machine learning model and trained it using a collection of spatially and temporally consistent inputs. After validation, they derived daily estimates of wildfire-induced PM_{2.5} concentrations across the contiguous U.S. over a 10 km-by-10 km grid from 2006 to 2020. In addition to the raw grid-level data, they summed the data at different geographic scales, including county, census tract, and ZIP code tabulation area (ZCTA). I average the daily county-level data from 2006 to 2019 to obtain a county-month level estimate. My primary measure of smoke exposure is the mean wildfire-induced PM_{2.5} concentrations at the county level for each month in this period.

In Section 6.3, I follow [Borgschulte et al. \(2022\)](#) and use smoke exposure data originally produced by the National Oceanic and Atmospheric Administration’s Hazard Mapping System (HMS) as a robustness check. The HMS utilizes observations from the Geostationary Operational Environmental Satellite, which generates imagery with a 1-km resolution for visible bands and a 2-km resolution for infrared bands, to identify fire and smoke emissions over

the contiguous U.S. (Ruminski et al., 2006). The primary measure of smoke exposure in this dataset is a daily indicator of a county’s coverage by a haze plume. I sum this to a monthly level to indicate the number of days a county is in a smog blanket each month.

4.2 Labour Market

I measure monthly labour market outcomes at the county level using data from the Local Area Unemployment Statistics (LAUS) program of the U.S. Bureau of Labor Statistics. LAUS provides county-level labour force counts for each month, including the numbers of persons who are unemployed, employed and in the labour force (the summation of the previous two). The primary dependent variable in this paper is the logarithmic transformation of the count of persons who are in the labour force. All my regressions in Section 5 are weighted by county-year level population counts. I also include a set of related labour variables in Section 6.3 for a robustness check.

4.3 Weather Data

I have two primary sources of weather-related information. Wind speed, wind direction and humidity data for the years 2006–2019 are obtained from the North American Regional Reanalysis (NARR) daily reanalysis data (Mesinger et al., 2006)¹. NARR includes raw data from weather stations on land, aircraft, satellites, radiosondes (essentially weather balloons), dropsondes (weather instruments released from aircraft), and other meteorological datasets. Wind and humidity data are reported for 32-by-32 kilometre grid-cells. I chose to use the wind data at 10 m level above ground and the humidity data at 2 m level above ground². The data for wind consists of two vectors: a “U-vector” for the East-West direction and a “V-vector” for

¹NARR data provided by Physical Sciences Laboratory (PSL) of National Oceanic and Atmospheric Administration (NOAA). See <https://psl.noaa.gov/data/gridded/data.narr.html> and <https://psl.noaa.gov/data/narr/> for more information and the NARR dataset itself. Accessed 2023-04-07.

²Other reported levels for the wind data including different pressure levels and tropopause. Other reported levels for the humidity data including different pressure levels and surface.

the North-South direction. For the U-vector, a positive number indicates East, while a negative number indicates West. The magnitude of the number indicates the wind speed (m/s) in that direction of the vector. This is the same for the V-vector, where North is represented by a positive number.

I first compound the two vectors into a single one to obtain one metric that represents the daily wind conditions at each grid point. Next, I identify intersections between grid-cell centroids and county polygons (meaning I determine which county the different centroids fall into). In this way, the centroids serve as different weather stations within a county. I averaged the wind conditions and humidity data to the county-month level. At last, I quantify the “wind direction” variable via the angle degree between the monthly averaged wind vector and the South wind vector, as shown in Figure 3.

I obtain temperature and precipitation data from [Schlenker and Roberts \(2009\)](#), which produced county-day level weather data from PRISM ([PRISM Climate Group, 2022](#)), where total daily precipitation and daily maximum and minimum temperatures are reported for 2.5-by-2.5 mile grid-cells encompassing the contiguous United States. I calculate a county-month measurement by averaging the daily measurements in each county.

4.4 Link Reservation to County

I use the Census Bureau’s 2021 Crosswalk file ³ to directly associate reservations by name and code with their containing counties. The file contained a crosswalk between 495 counties (FIPS code) and 396 reservations (American Indian Area code) in the contiguous U.S. Additional information includes the corresponding 1,214 census tract codes, ethnic population, and area.

Significant overlap exists between counties and reservations. Each reservation may span multiple counties. In addition, each county may overlap with one or more reservations. Consequently, when this occurs, the characteristics of the county and the reservation do not correspond.

³Many thanks to Dr. Donn Feir for kindly providing this file.

To solve this issue, I utilized the simplest method possible. I designate 1 to a dummy variable if a county contains a reservation (partial or complete) and 0 otherwise. I recognize that population and area would be the most common basis for weighting in general. In this instance, however, wildfire exposure and labour market data are not distributed proportionally to population or land area. Using population or area as a weighting factor is therefore not a flawless solution to the problem that counties and reservations do not correspond exactly.

4.5 Summary Statistics

Table 1 presents summary statistics at the county-month level for both reservation counties and non-reservation counties. The results of t-test between them are reported in the last column. The whole sample includes 522,144 observations of monthly labour participation record across 3,108 counties in the continental US ⁴. There are significant variations in all variables between reservation and non-reservation counties.

⁴Depending on the availability of controls and singletons in the panel data, observations might vary across specifications.

Chapter 5

Empirical Methodology

5.1 Wildfire Smoke and Labour Market Outcomes

To estimate the effect of air pollution on labour market outcomes, it is essential to rule out potential confounding factors influencing this relationship. For example, economic activity could determine both the performance of a labour market and the presence of air pollution in a given area. Moreover, as stated in Section 2.2, existing research has generally focused on particular industries or regions, which typically raises concerns regarding the national representativeness of the studies' results. A natural or quasi-natural experiment applicable to the whole country would be a solution to this challenge.

I use variation in wildfire smoke exposure to identify the causal effects of air pollution shocks on labour markets. Wildfire smoke plumes are a natural source of air pollution and travel hundreds or even thousands of miles downwind across the country (as shown in Figure 1), allowing me to distinguish the effects of smoke exposure separately from direct damages caused by wildfire burns. Figure 2 maps the mean of wildfire-induced PM_{2.5} concentration of each U.S. county in each year of the 2006-2019 sample period. As seen in the figure, the distribution of wildfire smoke varies yearly, which may be related to the meteorological conditions. Almost all areas of the continental U.S., except for the southern part of the Mountain Division, have been ravaged by wildfire smoke in different years.

My goal is to estimate the effect of exposure to PM2.5 from wildfire smoke on labour force participation, controlling for any potential confounding variables. I model this relationship using the following regression equation:

$$\log(\text{LF})_{cmy} = \beta \text{Smoke}_{cmy} + X'_{cmy} \gamma + \alpha_{cmy} + \alpha_{sm} + \epsilon_{cmy}, \quad (5.1)$$

where the dependent variable is the logarithmic transformation of the number of persons in the labour force in county c in month m and year y . The parameter of interest is β , the coefficient on monthly wildfire-induced PM2.5 levels.

There is well-established evidence that meteorologic conditions influence both pollution (Daly and Zannetti, 2007; Deryugina et al., 2019) and labour (Jessoe et al., 2018; Letta and Tol, 2019). I follow Deryugina et al. (2019) and control for a flexible function of temperature, precipitation and humidity. I generate indicators for monthly maximum temperatures falling into one of seventeen bins, ranging from -15 degrees Celsius or less to 30 degrees Celsius or more, with 15 intermediate bins spanning 3 degrees Celsius each. I do the same for minimum temperatures. I generate indicators for deciles of monthly precipitation and humidity. Then, I generate a set of indicators for all potential interactions among these variables and include it in all my regressions as X'_{cmy} . My estimates are robust to additional lag terms of weather controls (Table 10) or omitting weather controls entirely (Table 8). These findings support the hypothesis that my estimates are not driven by unobserved climatic variables that are correlated with both wind conditions and labour.

Following Borgschulte et al. (2022), my estimates also include county-by-month-by-year (α_{cmy}) and state-by-month (α_{sm}) linear time trends controls. The α_{cmy} controls for county-specific linear time trends in the regression. α_{sm} controls for any seasonal correlation between pollution, wind conditions, and labour participation, allowing this correlation to vary by state. As with weather controls, I estimate alternative specifications with varying fixed effects to demonstrate the robustness of my results. I weight regressions by county-year level population

counts^{1 2} and cluster all standard errors at the county level. My results are robust to different clustering choices.

I explore the robustness of my results to a variety of additional specifications including different definition of wildfire smoke (Table 6), labour outcome variables (Table 7), fixed effects (Table 8), standard error clusters (Table 9) and lag terms of weather (Table 10). The Section 6.3 provides detailed introduction about these checks.

5.2 Instrumental Variables Estimation

I recognize that wildfire smoke is not generated at random and that measurement errors are plausible. Thus, the preceding specification may not completely eliminate endogeneity concerns due to the omission of time-varying county-level factors. For instance, agricultural activity can affect both wildfire smoke and labour force participation. In this case, β would be subject to bias in favour of the direct impact of pollution on labour. To address these endogeneity concerns, I instrument wildfire smoke with wind speed and wind direction. Specifically, I estimate the following 2SLS specification:

$$\text{Smoke}_{cmy} = \Phi(\text{Wind}_{cmy}^S; \text{Wind}_{cmy}^D) + X'_{cmy}\gamma + \alpha_{cmy} + \alpha_{sm} + \epsilon_{cmy}, \quad (5.2)$$

$$\log(\text{LF})_{cmy} = \beta^{IV} \widehat{\text{Smoke}}_{cmy} + X'_{cmy}\gamma + \alpha_{cmy} + \alpha_{sm} + \epsilon_{cmy}, \quad (5.3)$$

where $\log(\text{LF})_{cmy}$ is again the logarithmic transformation of the number of person in the labour force in county c in month m and year y , and Φ is a parametric but flexible function of wind that considers both the effect of wind speed and wind direction as well as their interaction on wildfire smoke. The definitions of wind speed and wind direction is depicted in Figure 3, where wind speed is the norm of the wind vector and wind direction is the angle degree between the

¹Population data provided by Surveillance, Epidemiology, and End Results (SEER) Database (SEER, 2022). See <https://seer.cancer.gov> and <https://seer.cancer.gov/popdata/download.html> for more information and the SEER U.S. Populations dataset itself. Accessed 2023-04-09.

²County population control allows me to use the logarithm transformation of the number of people as the labour outcome variable in the linear fixed effects model.

wind vector and the South wind. $\widehat{\text{Smoke}}_{cmy}$ is the corresponding prediction from the first stage (Equation 5.2), I include the same set of weather controls and fixed effects as Equation 5.1.

The model specification described in Equations 5.2 and 5.3 is motivated by previous results in the literature as well as by the data. In Figure 4, I use Massachusetts as an example to show the relationship between wind direction and wildfire smoke. It is clear that PM2.5 levels are higher when the wind direction interval is $[0, 100]$. As a northeastern coastal province, the southwest direction is exactly the direction in which Massachusetts borders other continental areas. This also coincides Figure 2, where wildfire smoke from the Midwest enters Massachusetts from the west and southwest. To account for the potential complementarity between wind direction and wind speed, I further specify that

$$\Phi(\text{Wind}_{cmy}^S; \text{Wind}_{cmy}^D) = \sum_{q \in Q} \delta_q \cdot (\text{Wind}_{cmy}^S \times \mathbb{1}\{\text{Wind}_{cmy}^D = q\}), \quad (5.4)$$

where Q represents the set of potential quadrants $Q = \{NW, NE, SW, SE\}$ and $\mathbb{1}(\cdot)$ is an indicator function.

The essential identifying assumption when using wind as an instrument for air pollution is that, after controlling for weather variables, county-specific linear time trends and fixed effects, the interaction between wind speed and wind direction only influences labour participation via its influence on air pollution.

One concern about using wind speed as part of the instrument is that wind speed might directly affect the labour supply outdoors. Therefore, the exclusion restriction would be violated if wind speed affected labour behaviour. Despite the fact that some regions experience several days of seasonal gusty weather, my data sample indicates that the average monthly wind speed is moderate. In fact, the average wind speed throughout the duration of the analysis is 1.58 m/s (around 3 knots), which, according to the Beaufort Wind Scale ³, is classified as *Light Air* with no significant impact on the land. In addition, the 99th percentile of wind speed in my data is

³An empirical measure that relates wind speed to observed conditions at sea or on land. See <https://www.spc.noaa.gov/faq/tornado/beaufort.html> for more information. Accessed 2023-04-09.

4.71 m/s (around 9.16 knots), which is considered as *Gentle Breeze* in which leaves and small twigs are constantly moving.

Chapter 6

Results

6.1 Wildfire Smoke and Labour Market Outcomes

I first estimate the effect of wildfire smoke on the log labour force count using ordinary least squares (OLS) as a comparison to the results of the instrumental variables specification. Table 2 presents the results of estimating Equation 5.1. Column 1 shows the estimated coefficient without including any county-specific linear time trends or fixed effects. The result suggests that an additional one unit in the monthly average wildfire-induced PM2.5 is associated with a decrease in the number of labour force by 2.94%, which is statistically significant at the 10% level. Column 2 flexibly controls for temperature and other weather variables. Columns 3–5 display the results after including county-specific linear time trends and various sets of fixed effects. Column 3 shows that an additional unit in the monthly average wildfire-induced PM2.5 leads to a 0.01% increase in the labour force count after including county-time fixed effects. My baseline specification includes a full set of county-specific linear time trends and fixed effects and is depicted in Column 4.

Next, given that wildfire smoke might not be randomly generated, I implement an instrumented variable strategy to rule out any remaining time-varying confounders that could affect both wildfire smoke and labour. Table 3 reports my main IV strategy estimates, where I use the interaction of wind speed and wind direction as an exogenous shock to wildfire smoke. The

first stage estimate, in Column 1, shows that my instrument strongly predicts wildfire smoke. The IV estimate, in Column 3, implies that one additional unit in the wildfire-induced PM2.5 concentration causes the number of people in the labour force fall by 0.55%. This result is consistent with previous studies. For example, (Borgschulte et al., 2022) found that a 1 $\mu\text{g}/\text{m}^3$ increase in quarterly PM2.5 concentrations reduces labour force participation by 791 individuals per million people.

6.2 Heterogeneity by Reservation and Region

To shed light on the conditions under which labour markets are the most sensitive to pollution shocks, and to compare the relationship between the magnitude of the “income effect” and the “substitution effect” under different scenarios, I explore how the effects of wildfire pollution vary by Indigenous reservation status. To do this, I create an indicator for whether a county contains a reservation (or reservations) within its boundaries. This indicator variable is 1 in five cases: a county alone is equivalent to a reservation; a county is part of a reservation; a county is part of multiple reservations; a part of a county is a reservation; and a part of a county is multiple reservations. I estimate heterogeneity in the labour supply effects of smoke exposure by region. Table 4 represents the results for all the county sample, and Table 5 shows the results for reservations ¹.

In Table 4, the estimated coefficients of wildfire smoke for counties in the Northeast and Midwest regions of the U.S. are -0.0013 and -0.0031, respectively. The former is statistically significant at the 5% level and the latter is statistically significant at the 1% level. This result suggests that the “substitution effect” of wildfire smoke on labour supply dominates in these two regions. The “income effect” is either in the same direction as the “substitution effect” or in the opposite direction, with a smaller magnitude. For the Western and Southern regions, the effects are not statistically significant, indicates that the “income effect” is negative and of comparable magnitude to the “substitution effect”.

¹In the context, the reservations mean the counties with the indicator variables equal to 1.

In Table 5, on the other hand, the situation is not quite the same for the reservations. The estimated coefficient for all reservations is 0.0031, not statistically significant, suggesting that the “income effect” is opposite and similar in magnitude to the “substitution effect”. This relationship also applies to reservations located in the Northeast and West regions, where the estimated coefficients are 0.0003 and 0.0032 respectively. Notably, I observe a strong “substitution effect” in reservations located in the Midwest and a strong “income effect” in reservations located in the South region. The estimated coefficient for the Midwest is -0.0048, implies that one additional unit in the wildfire-induced PM2.5 concentration causes a decrease in the number of labour force participants by 0.4788%. The negative utility of wildfire smoke is significant, causing people to considerably reduce their labour supply. For the South region, the estimated coefficient is 0.012, which implies that one additional unit in the wildfire-induced PM2.5 concentration causes an increase in the number of labour force participants by 1.2072%. The negative utility of wildfire smoke is significant, causing people to considerably reduce their labour supply. A possible explanation is that wildfire smoke significantly lowers people’s marginal income, making it necessary to increase labour supply to maintain the same level of income while enduring air pollution.

6.3 Robustness Checks

I conduct a series of robustness tests and the results are shown in Table 6 to Table 10. In Table 6, I replace the primary independent variable, wildfire smoke, in the baseline model with the number of smoke days per month in each county. In Column 1, I use smoke exposure data from the National Oceanic and Atmospheric Administration’s Hazard Mapping System (HMS). In this setting, a day is defined as a “smoke day” if a county is completely covered in smoke on satellite images. In the Column 2, I calculate the number of days per month that the PM2.5 concentration is greater than zero for each county in the primary data set. The results in both columns are statistically significantly negative at the 1% and 5% levels, respectively, demonstrating the robustness of my benchmark model.

In Table 7, I perform robustness tests on the dependent variable. I selected four different labour output variables to replace the logarithm transformation of the number of labour force participation. The variables in Column 1 through 4 are: the logarithm transformation of the number of unemployed people, the logarithm transformation of the number of employed, the unemployment rate and the labour force participation rate. The unemployment rate is the ratio of the number of unemployed to the number of people in the labour force. The labour force participation rate is the ratio of the number of people in the labour force to the population aged 16 to 60 in that county. As can be seen from the table, wildfire smoke has a significant negative effect on the number of employed people and the labour force participation rate, while it does not have a statistically significant effect on the number of unemployed people or the unemployment rate.

I report a series of regression results based on different fixed effects in Table 8 and clustering standard errors in Table 9. Except for Column 2 of Table 8, these results are all statistically significant at conditional levels. To detect the lingering effect of wildfire smoke on the labour market, I add the first and second lag terms of the weather control variables to the baseline model. The results are shown in Table 10, and they are all statistically significant at the 1% level.

Chapter 7

Discussion

7.1 Potential Mechanisms

This paper attempts to demonstrate the negative impact of air pollution on the economy and society by measuring the impact of wildfire smoke on labour supply. In line with the literature, this paper does find that wildfire smoke is associated with lower labour force participation at the county level. This paper further decomposes the “substitution effect” and the “income effect” of wildfire smoke on labour by constructing a partial equilibrium model. At this section, I propose possible paths of influence mechanisms for each of these two effects.

The “substitution effect” refers to the phenomenon that an increase in wildfire smoke, or air pollution, leads to an increase in the negative utility of workers, which reduces the supply of labour time. This increase in negative utility may have multiple causes. As I discuss in [Section 2.2](#), health factors are among the most likely causes. Although wildfire smoke is intuitively an outdoor pollution, its main component, fine particulate matter, allows it not only to enter indoor areas, but also to penetrate into the human body and have an effect on all human functions. Thus, the health effects of wildfire smoke are not limited to outdoor workers. The resulting adverse physical reactions, including respiratory illnesses, may affect the worker’s time supply. In addition, mental health factors cannot be ignored. Wildfire smoke that obscures the sky not only has a visual impact, but can also be psychologically depressing. Episodes of mental illness

can also lead to a reduction in labour supply.

The “income effect” of wildfire smoke indicates that wildfire smoke reduces people’s marginal income, making it necessary for workers to increase labour supply to maintain the same level of income. Of course, this effect is more pronounced for specific job groups, such as casual or temporary laborers. For them, there is a strong positive correlation between working hours and income levels. In general, in less developed areas, people care more about income levels, even more than health factors. This hypothesis is generally consistent with my results. In the Southern region of the United States, the “income effect” of wildfire smoke significantly exceeds the “substitution effect”, whether it is on a reservation or not. This suggests that workers in the South care more about income levels and need to work more to support their families the more severe the smoke is. This hypothesis is also generally consistent with the regression results for most reservations. In the Northeast and West, the “substitution effect” dominates the full sample. But when I focus on the reservations, the “substitution effect” gives way to the “income effect”. This shift is even more pronounced in the South, where the overall effect becomes statistically significant positive when focusing only on reserves. The only difference is in the Midwest, where the “substitution effect” is instead enhanced in the reservation. This may be related to the production structure of the Midwest or to people’s income perceptions. In conclusion, the effect of wildfire smoke on labour supply shows significant variability across regions and reservation-non-reservation sites.

7.2 Limitations

The limitations of this paper come mainly from the data possibilities. For the testing of substitution effects, health data and mental health data are crucial. The National Center for Health Statistics (NCHS) of Centers for Disease Control and Prevention (CDC) in the U.S. provides detailed geocoded death data, including fetal deaths, newborn deaths, and elderly deaths. Unfortunately, this data is not available to personnel located outside the United States. In the version available for public download on the Web, data less than 10 for each county are erased

or symbolically provided as random numbers. Since my regression analysis is based on the county-month level, such data quality does not allow reliable conclusions to be drawn. The same privacy protection treatment also prevents other CDC databases from being used by me, such as National Health Interview Survey (NHIS) and National Health and Nutrition Examination Survey (NHANES).

The population data used as weights in this paper are from the Surveillance, Epidemiology, and End Results (SEER) Database. This database also provides detailed, geocoded records about cancer. Unfortunately, this database currently includes only 21 states and several metropolitan areas. To ensure the integrity of the cross-section, I did not end up selecting this data.

The Behavioral Risk Factor Surveillance System (BRFSS) is a very common choice when it comes to mental health. Unfortunately, its county-level data are included from 2006 to 2013, and its sample of counties is only those areas where more than 500 people were interviewed, an average of 250 per year. Compared to my final data of 3,108 counties, this sample is too small and unrepresentative. As with much of the aforementioned data, the BRFSS can be used perfectly at the state level.

In terms of mechanistic tests of the “income effect”, county-level income and production structure data are only available as precise as quarterly, which can be found in Quarterly Workforce Indicators (QWI) of the Census Bureau of the United States. This is the next direction this paper could take, examining the effects of wildfire smoke on labour supply at the quarterly level. Also, use the richer labour data from QWI to test for differences in the “income effect” across regions and reservations.

Chapter 8

Conclusion

This paper provides empirical evidence of the relationship between wildfire smoke and labour supply. This paper constructs a partial equilibrium model between the two and uses instrumental variables combining wind speed and wind direction to provide more robust results. The paper also focuses on the discrepancy between reserved and off-reserve areas.

My results find that more severe wildfire smoke is associated with lower county-level labour force participation. I decompose this relationship into a “substitution effect” and an “income effect” based on the partial equilibrium model. The total effect of wildfire smoke on labour supply depends on the direction and magnitude of these two effects. Overall, the “substitution effect” dominates in most cases, with denser wildfire smoke leading workers to reduce their labour supply. In contrast, I observe a stronger “income effect” in less developed areas, such as the South region and the reservations. Wildfire smoke reduces people’s marginal income, making it necessary for workers to increase their labour supply to maintain the same level of income.

These results arise from an identification strategy that uses wind speed and direction as instrumental variables for air pollution. Also, these data are robust to different definitions of wildfire smoke, various labour outcomes, a set of standard error clusters and lag terms of weather controls.

My findings have extensive ramifications for environmental policy. Historically, many in-

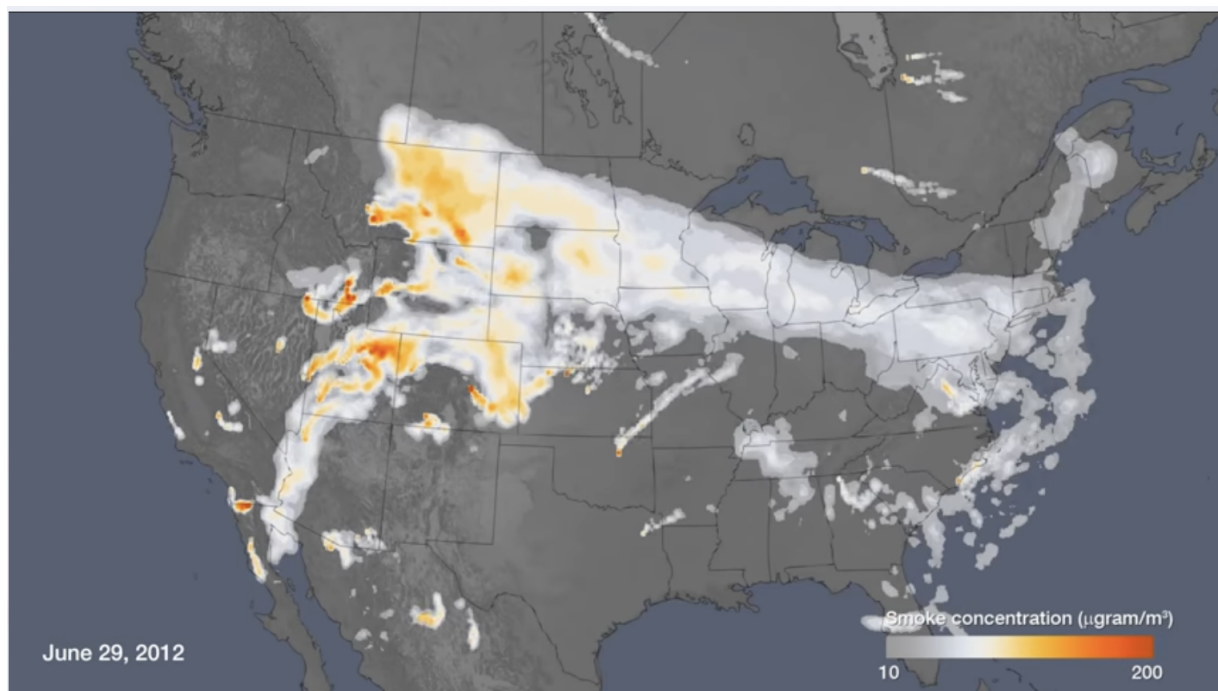
stitutions engaged in the formulation of environmental policy have regarded pollution damage resulting from lost labour market time as significantly less severe than the mortality costs of air pollution. My findings suggest that environmental policies that disregard or minimize the effects of air pollution on the labour market fail to account for significant costs and, consequently, may be ineffective. My findings also suggest that policies to address the labour-related effects of air pollution should be devised in a region-specific manner. People in less developed areas may endure a greater cost of pollution due to the fact that they may increase their own labour supply while simultaneously increasing their own exposure levels when pollution levels are high.

My findings have direct implications for the policy and management of wildfires. A significant implication of my findings is that smoke from wildfires generates a multitude of externalities. Local land use and fire management decisions can have repercussions for distant populations. These far-reaching effects necessitate greater coordination of fire policy, with an emphasis on averting the start and spread of wildfires. Beyond the traditional objective of protecting land and property exposed to fire in a given area, policies should take into account factors such as the quantity of smoke produced by a fire and whether the smoke plume will reach populated areas. Despite the fact that wildfires and pollution cannot be eliminated entirely, policies can mitigate the damage caused by these occurrences by assessing the full extent of their effects.

Appendix A

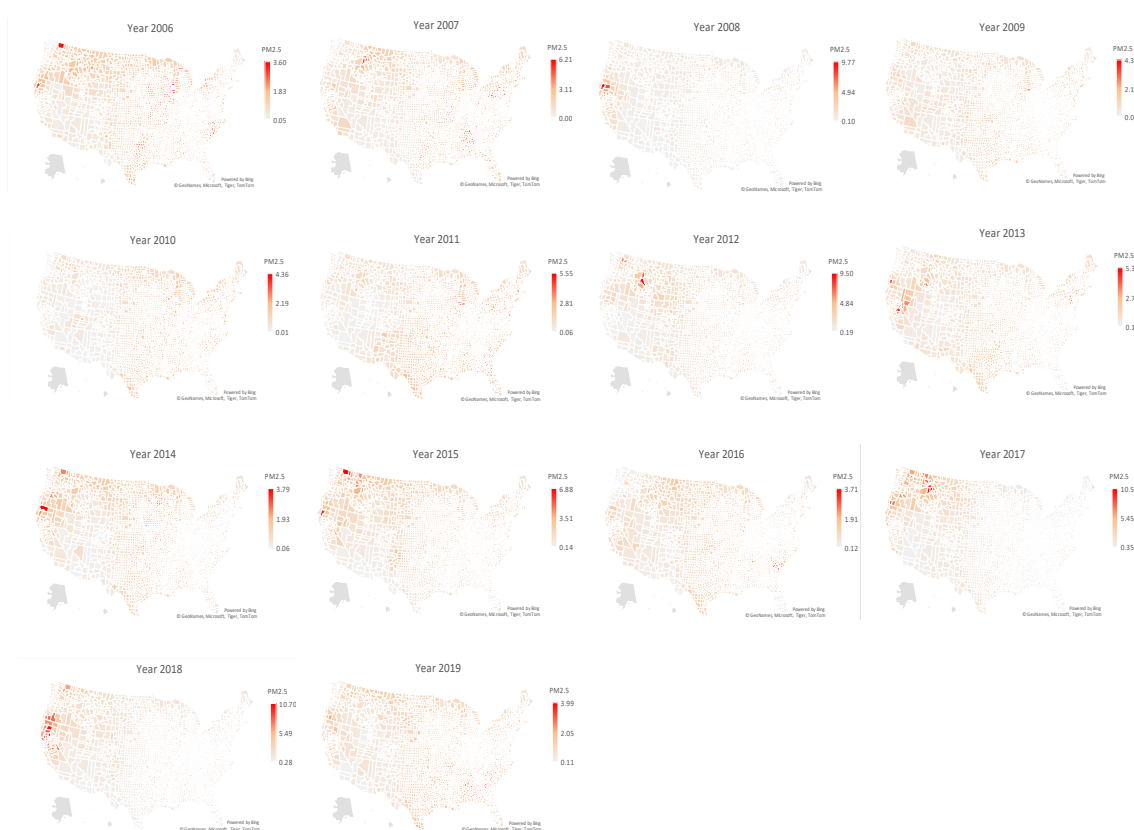
Tables and Additional Information

Figure 1: Fire and Smoke on June 29, 2012



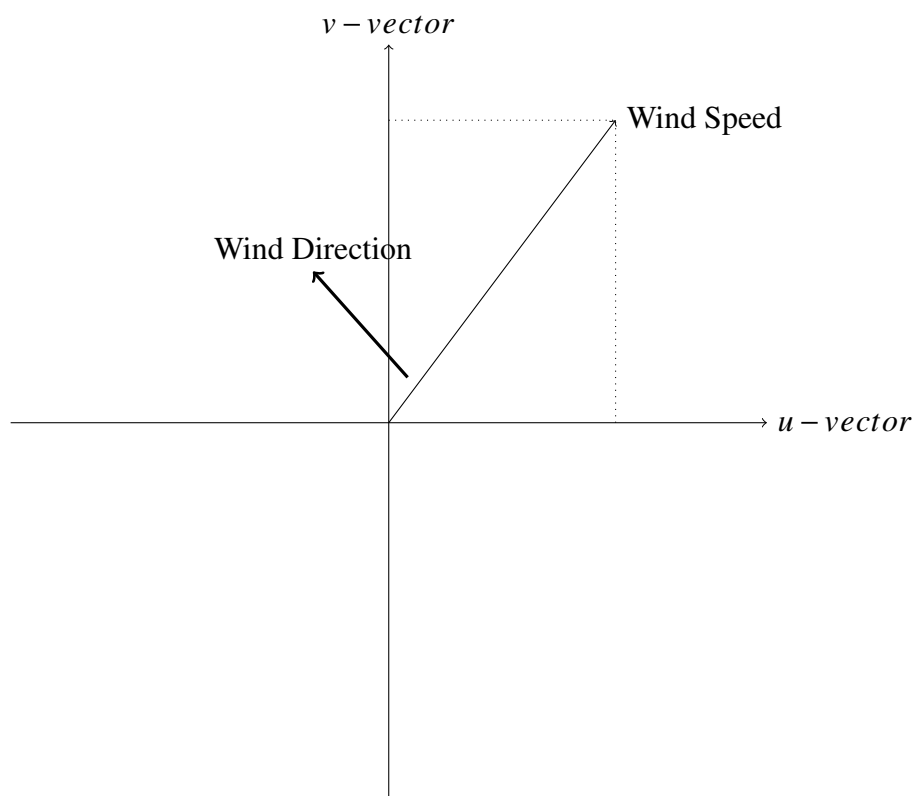
Note: This map depicts smoke patterns on June 29, 2012. The wildfires can be seen in Mountain Region of U.S. and the smoke plume reaches the east coast. Source: <https://www.arl.noaa.gov/hysplit/smoke-forecasting/>.

Figure 2: Annual average level of wildfire-induced PM2.5



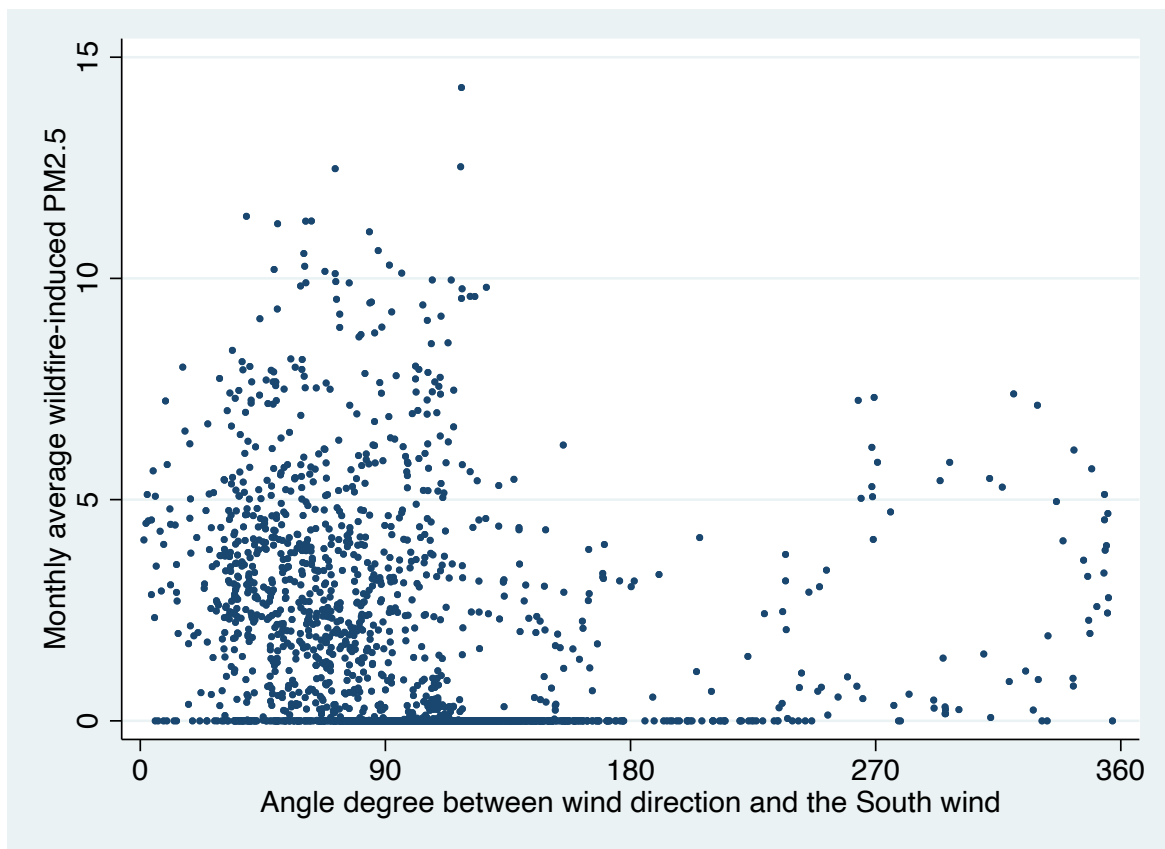
Note: This figure plots the annual average level of wildfire-induced PM2.5 in each county in the continental United States over the 2006-2019 sample period.

Figure 3: Definitions of Wind Speed and Wind Direction



Note: This graph depicts the definitions of wind speed and wind direction in this paper. Every wind vector includes two sub-vectors: u -vector and v -vector. The former represents the East-West axis, with arrow points to the East. The latter represents the North-South axis, with arrow points to the North. Wind Speed is the norm of the vector. Wind Direction is the angle degree between the wind vector and the South wind.

Figure 4: Wildfire-induced PM2.5 and wind direction in Massachusetts, 2006-2019



Note: This figure shows the relationship between wildfire-induced PM2.5 level and the wind direction in Massachusetts from 2006 to 2019. The wind direction is measured as the angle degree between the wind direction and the South wind. It is clear that most of the sample points with high pollution were concentrated in the $[0, 100]$ interval, indicating that wildfire smoke in this province is more severe when the wind comes from the southwest.

Table 1: Summary Statistics

	County			Difference
	All	Reservation	Non-reservation	
<i>Labour Market Outcome</i>				
No. of People in Labour Force (log)	9.5304 (1.48)	9.6821 (1.5318)	9.5017 (1.4683)	-0.1803*** (0.0058)
No. of People Employed (log)	9.4655 (1.4791)	9.6138 (1.53)	9.4374 (1.4676)	-0.1764*** (0.0057)
Unemployment Rate	6.2397 (3.0291)	6.5388 (3.35)	6.1830 (2.9610)	-0.3558*** (0.0124)
Labour Force Participation Rate	60.1021 (9.4159)	59.6723 (9.2043)	60.1835 (9.4533)	0.5112*** (0.035)
<i>Air Pollution</i>				
Wildfire Smoke (µg/m³)	1.5998 (2.314)	1.4012 (2.4691)	1.6374 (2.2815)	0.2362*** (0.0092)
Number of Smoke Days	2.1516 (4.2379)	2.2517 (4.5918)	2.1326 (4.1672)	-0.1191*** (0.0178)
<i>Wind Conditions</i>				
Wind Speed (m/s)	1.5801 (0.9691)	1.6743 (1.0233)	1.5623 (0.9574)	-0.112*** (0.0038)
Wind Direction	137.1843 (116.0288)	138.5819 (114.1981)	136.9195 (116.3706)	-1.6624*** (0.4332)
<i>Meteorology</i>				
Minimum Temperature (°C)	6.5130 (9.7371)	4.8143 (9.9528)	6.8354 (9.662)	2.0211*** (0.0375)
Maximum Temperature (°C)	19.0845 (10.3256)	17.5978 (10.9636)	19.3667 (10.1755)	1.7689*** (0.041)
Precipitation (mm)	2.7780 (1.9896)	2.4083 (2.2511)	2.8482 (1.928)	0.4399*** (0.0083)
Humidity (%)	70.1253 (12.8368)	66.9619 (17.004)	70.7246 (11.7887)	3.7627*** (0.0616)
<i>Demography</i>				
Population	100,521 (321,542.6)	131,166.3 (365,365.1)	94,713.38 (312,207.7)	-36,452.91*** (1,351.802)
Observations	522,144	83,160	438,984	-

Notes: Numbers are the average values at the county-month level from January 2006 to December 2019. Standard errors are reported in parentheses. The definitions of reservation and non-reservation county are given in Section 4.4. Their differences are reported in the last column. t-test (unequal variances) standard errors are reported in parentheses.

Table 2: Wildfire-induced PM2.5's Impact on Labour: OLS Estimation

	Log (Number of People in Labour Force)				
	(1)	(2)	(3)	(4)	(5)
Wildfire Smoke	-0.0294* (0.0160)	-0.0176** (0.0080)	0.0001*** (0.0000)	0.0001*** (0.0000)	-0.0000 (0.0000)
Observations	521746	520434	520434	520434	520434
Weather Controls		Y	Y	Y	Y
County $\times$ Month $\times$ Year FE			Y	Y	Y
State $\times$ Month FE				Y	
State $\times$ Year FE					Y

Notes: Regressions are at the county-month level. Monthly data from January 2006 to December 2019. The dependent variable is the logarithm transformation of the number of people in the labour force. The model is estimated using a OLS specification. The wildfire smoke is the wildfire-induced PM2.5 concentration level, measured in $\mu\text{g}/\text{m}^3$. I include flexible weather controls, county-specific linear time trends and state-time fixed effects. Please see Section 5.1 for details on these controls. Standard errors are clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Wildfire-induced PM2.5's Impact on Labour: Instrument Variable Model

	First Stage	Reduced Form	2SLS
	(1)	(2)	(3)
Wind Speed	-0.1242*** (0.0166)	0.0006*** (0.0001)	
Wind Speed $\times$ Dominant Wind in Quadrant 4	0.1294*** (0.0193)	-0.0011*** (0.0001)	
Wind Speed $\times$ Dominant Wind in Quadrant 3	0.1200*** (0.0313)	0.0010** (0.0004)	
Wind Speed $\times$ Dominant Wind in Quadrant 2	0.0603*** (0.0207)	-0.0000 (0.0002)	
Wildfire Smoke			-0.0055*** (0.0012)
Kleibergen-Paap F	-	-	21.901
Observations	520,664	520,622	520,622
Weather Controls	Y	Y	Y
County $\times$ Month $\times$ Year FE	Y	Y	Y
State $\times$ Month FE	Y	Y	Y
Population Weight	Y	Y	Y

Notes: Regressions are at the county-month level. Monthly data from January 2006 to December 2019. The dependent variable in column 1 is the monthly average wildfire-induced PM2.5 concentration. The logarithm transformation of the number of people in the labour force is the dependent variables in column 2 and 3. The first two models are estimated using a OLS specification and the last one is estimated using an IV specification, where the instrument variables are the interactions between the monthly average wind speed and wind directions. The wildfire smoke is measured in $\mu\text{g}/\text{m}^3$. I include flexible weather controls, county-specific linear time trends and state-time fixed effects. Please see Section 5.1 for details on these controls. All regressions are weighted by the population counts at the county-year level. Standard errors are clustered at the county level. The Kleibergen-Papp F-test is reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Wildfire-induced PM2.5's Impact on Labour: By Region

	All	Northeast	Midwest	South	West
	(1)	(2)	(3)	(4)	(5)
Wildfire Smoke	-0.0055*** (0.0012)	-0.0013** (0.0006)	-0.0031*** (0.0005)	0.0021 (0.0020)	-0.0003 (0.0019)
Kleibergen-Paap F	21.901	26.789	71.59	26.785	5.305
Observations	520,622	36,067	176,879	237,667	68,781
Weather Controls	Y	Y	Y	Y	Y
County $\times$ Month $\times$ Year FE	Y	Y	Y	Y	Y
State $\times$ Month FE	Y	Y	Y	Y	Y
Population Weight	Y	Y	Y	Y	Y

Notes: Regressions are at the county-month level. Monthly data from January 2006 to December 2019. The dependent variables are the logarithm transformation of the number of people in the labour force. The instrument variables are the interactions between the monthly average wind speed and wind directions. The wildfire smoke is measured in $\mu\text{g}/\text{m}^3$. The region classification is based on the U.S. Census Bureau. I include flexible weather controls, county-specific linear time trends and state-time fixed effects. Please see Section 5.1 for details on these controls. All regressions are weighted by the population counts at the county-year level. Standard errors are clustered at the county level. The Kleibergen-Papp F-test is reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Wildfire-induced PM2.5's impact on labour: By Reservation and Region

	Reservations	Northeast	Midwest	South	West
	(1)	(2)	(3)	(4)	(5)
Wildfire Smoke	0.0031 (0.0032)	0.0003 (0.0013)	-0.0048*** (0.0014)	0.0120*** (0.0039)	0.0032 (0.0035)
Kleibergen-Paap F	2.853	5.765	16.48	10.415	4.793
Observations	82,570	4,377	24,265	25,001	27,570
Weather Controls	Y	Y	Y	Y	Y
County $\times$ Month $\times$ Year FE	Y	Y	Y	Y	Y
State $\times$ Month FE	Y	Y	Y	Y	Y
Population Weight	Y	Y	Y	Y	Y

Notes: Regressions are at the county-month level. Monthly data from January 2006 to December 2019. The dependent variables are the logarithm transformation of the number of people in the labour force. The instrument variables are the interactions between the monthly average wind speed and wind directions. The wildfire smoke is measured in $\mu\text{g}/\text{m}^3$. The indicator variable for reservation is based on whether a county contains a reservation, either in part or in full. The region classification is based on the U.S. Census Bureau. I include flexible weather controls, county-specific linear time trends and state-time fixed effects. Please see Section 5.1 for details on these controls. All regressions are weighted by the population counts at the county-year level. Standard errors are clustered at the county level. The Kleibergen-Papp F-test is reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Robustness Check: By Definition of Wildfire Smoke

	Log (Number of People in Labour Force)	
	(1)	(2)
Number of Smoke Days	-0.0041*** (0.0014)	
Number of Days with Positive PM2.5		-0.0018** (0.0008)
Kleibergen-Paap F	10.348	12.685
Observations	483,441	520,622
Weather Controls	Y	Y
County $\times$ Month $\times$ Year FE	Y	Y
State $\times$ Month FE	Y	Y
Population Weight	Y	Y

Notes: Regressions are at the county-month level. Monthly data from January 2006 to December 2019. The dependent variables are the logarithm transformation of the number of people in the labour force. The instrument variables are the interactions between the monthly average wind speed and wind directions. The number of smoke day is defined from the HMS dataset. The number of smoke day is defined from the HMS dataset. The number of days with positive PM2.5 level is calculated with the primary dataset. I include flexible weather controls, county-specific linear time trends and state-time fixed effects. Please see Section 5.1 for details on these controls. All regressions are weighted by the population counts at the county-year level. Standard errors are clustered at the county level. The Kleibergen-Papp F-test is reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Robustness Check: By Labour Outcome Specification

	Log (No. UE)	Log (No. EM)	UE Rate	LF Participation Rate
	(1)	(2)	(3)	(4)
Wildfire Smoke	-0.0059 (0.0186)	-0.0068*** (0.0021)	0.1131 (0.1292)	-0.2359*** (0.0737)
Kleibergen-Paap F	21.901	21.901	21.901	21.901
Observations	520,434	520,434	520,434	520,434
Weather Controls	Y	Y	Y	Y
County $\times$ Month $\times$ Year FE	Y	Y	Y	Y
State $\times$ Month FE	Y	Y	Y	Y
Population Weight	Y	Y	Y	Y

Notes: Regressions are at the county-month level. Monthly data from January 2006 to December 2019. The dependent variables are the logarithm transformation of the number of people unemployed in column 1, the logarithm transformation of the number of people employed in column 2, the unemployment rate in column 3 and the labour force participation rate in column 4. The instrument variables are the interactions between the monthly average wind speed and wind directions. I include flexible weather controls, county-specific linear time trends and state-time fixed effects. Please see Section 5.1 for details on these controls. All regressions are weighted by the population counts at the county-year level. Standard errors are clustered at the county level. The Kleibergen-Papp F-test is reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: Robustness Check: By Fixed Effects

	Log (Number of People in Labour Force)				
	(1)	(2)	(3)	(4)	(5)
Wildfire Smoke	-0.2776* (0.1611)	0.1385 (0.2343)	-0.0055*** (0.0012)	-0.0055*** (0.0012)	-0.0014* (0.0008)
Kleibergen-Paap F	63.83	41.839	21.928	21.901	20.662
Observations	521,746	520,434	520,434	520,434	520,434
Weather Controls		Y	Y	Y	Y
County $\times$ Month $\times$ Year FE			Y	Y	Y
State $\times$ Month FE				Y	
State $\times$ Year FE					Y

Notes: Regressions are at the county-month level. Monthly data from January 2006 to December 2019. The dependent variable is the logarithm transformation of the number of people in the labour force. The instrument variables are the interactions between the monthly average wind speed and wind directions. Column 1 contains no fixed effects. I gradually include flexible weather controls, county-specific linear time trends and state-time fixed effects in Column 2 to 4. I replace the state-month fixed effect with state-year fixed effect in Column 5. Column 4 is my baseline specification. All regressions are weighted by the population counts at the county-year level. Standard errors are clustered at the county level. The Kleibergen-Papp F-test is reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9: Robustness Check: By Clustered Standard Errors

	Log (Number of People in Labour Force)					
	(1)	(2)	(3)	(4)	(5)	(6)
Wildfire Smoke	-0.0055* (0.0032)	-0.0055** (0.0022)	-0.0055* (0.0023)	-0.0055** (0.0021)	-0.0055* (0.0023)	-0.0055** (0.0021)
Kleibergen-Paap F	1.908	4.809	30.812	8.286	30.812	8.286
Observations	520,434	520,434	520,434	520,434	520,434	520,434
Weather Controls	Y	Y	Y	Y	Y	Y
County $\times$ Month $\times$ Year FE	Y	Y	Y	Y	Y	Y
State $\times$ Month FE	Y	Y	Y	Y	Y	Y
Population Weight	Y	Y	Y	Y	Y	Y
County + Region-By-Month	Y					
County + State-By-Month		Y				
County + Region			Y			
County + State				Y		
Region					Y	
State						Y

Notes: Regressions are at the county-month level. Monthly data from January 2006 to December 2019. The dependent variables are the logarithm transformation of the number of people in the labour force. The instrument variables are the interactions between the monthly average wind speed and wind directions. I include flexible weather controls, county-specific linear time trends and state-time fixed effects. Please see Section 5.1 for details on these controls. All regressions are weighted by the population counts at the county-year level. Standard errors are clustered at different levels as shown in the table. The Kleibergen-Papp F-test is reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 10: Robustness Check: By Weather Lags

	Log (Number of People in Labour Force)	
	(1)	(2)
Wildfire Smoke	-0.0061*** (0.0012)	-0.0053*** (0.0012)
Kleibergen-Paap F	26.001	24.383
Observations	516,864	513,299
Weather Controls	Y	Y
County $\times$ Month $\times$ Year FE	Y	Y
State $\times$ Month FE	Y	Y
Population Weight	Y	Y
First Lag of Weather	Y	Y
Second Lag of Weather		Y

Notes: Regressions are at the county-month level. Monthly data from January 2006 to December 2019. The dependent variables are the logarithm transformation of the number of people in the labour force. The instrument variables are the interactions between the monthly average wind speed and wind directions. I include flexible weather controls, county-specific linear time trends and state-time fixed effects. Please see Section 5.1 for details on these controls. Column 1 includes the first lag of weather controls. Column 2 includes the first two lags of weather controls. All regressions are weighted by the population counts at the county-year level. Standard errors are clustered at the county level. The Kleibergen-Papp F-test is reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix B

The Partial Equilibrium Model

This appendix contains the proofs and derivations omitted from the main body of the paper.

The Lagrangian function of individual utility is

$$\mathcal{L} = u(c, h|\alpha) + \lambda(wh + y - pc) \quad (\text{B.1})$$

The first order derivatives of Equation B.1 with respect to consumption c and working time h yields:

$$u_c(c, h|\alpha) = \lambda p \quad (\text{B.2})$$

$$-u_h(c, h|\alpha) = \lambda w \quad (\text{B.3})$$

Derive Equations B.2 and B.3 with respect to the air quality α :

$$u_{cc} \cdot \frac{dc}{d\alpha} + u_{ch} \cdot \frac{dh}{d\alpha} = \frac{\partial \lambda}{\partial \alpha} \cdot p \quad (\text{B.4})$$

$$-u_{hc} \cdot \frac{dc}{d\alpha} - u_{hh} \cdot \frac{dh}{d\alpha} = \frac{\partial \lambda}{\partial \alpha} \cdot w \quad (\text{B.5})$$

Given that the sign of the mixed partial derivatives of c and h , u_{hc} or u_{ch} , is not clear, Equations

B.4 and B.5 can be simplified as:

$$u_{cc} \cdot \frac{dc}{d\alpha} + u_{c\alpha} = \frac{\partial \lambda}{\partial \alpha} \cdot p \quad (\text{B.6})$$

$$-u_{h\alpha} - u_{hh} \cdot \frac{dh}{d\alpha} = \frac{\partial \lambda}{\partial \alpha} \cdot w \quad (\text{B.7})$$

Further rearrangement of Equations B.6 and B.7:

$$\frac{dc}{d\alpha} = \frac{\frac{\partial \lambda}{\partial \alpha} \cdot p - u_{c\alpha}}{u_{cc}} \quad (\text{B.8})$$

$$\frac{dh}{d\alpha} = \frac{\frac{\partial \lambda}{\partial \alpha} \cdot w + u_{h\alpha}}{-u_{hh}} \quad (\text{B.9})$$

From Equation 3.3, I have $u_{h\alpha} = -D_{h\alpha}$ and $u_{hh} = -D_{hh}$. Replacing the two terms in Equation B.9 yields:

$$\frac{dh}{d\alpha} = \frac{-D_{h\alpha} + \frac{\partial \lambda}{\partial \alpha} \cdot w}{D_{hh}} \quad (\text{B.10})$$

This is the same expression as Equation 3.6. From the constraint budget line (Equation 3.4), I have

$$\frac{dc}{d\alpha} = \frac{dh}{d\alpha} \cdot \frac{w}{p} \quad (\text{B.11})$$

From Equation B.8, I have

$$\frac{\partial \lambda}{\partial \alpha} = \frac{\frac{dc}{d\alpha} \cdot u_{cc} + u_{c\alpha}}{p} \quad (\text{B.12})$$

Substituting Equation B.11 into Equation B.12 yields:

$$\frac{\partial \lambda}{\partial \alpha} = \frac{\frac{dh}{d\alpha} \cdot \frac{w}{p} \cdot u_{cc} + u_{c\alpha}}{p} \quad (\text{B.13})$$

Substituting Equation B.9 into Equation B.13 yields:

$$p \cdot \frac{\partial \lambda}{\partial \alpha} = \frac{\frac{\partial \lambda}{\partial \alpha} \cdot w + u_{h\alpha}}{-u_{hh}} \cdot \frac{w}{p} \cdot u_{cc} + u_{c\alpha} \quad (\text{B.14})$$

Rearranging Equation B.14 yields:

$$\frac{\partial \lambda}{\partial \alpha} = \frac{p \cdot u_{c\alpha} \cdot u_{hh} - w \cdot u_{cc} \cdot u_{h\alpha}}{w^2 \cdot u_{cc} + p^2 \cdot u_{hh}}. \quad (\text{B.15})$$

This is the same expression as Equation 3.7.

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