Title

Impact of Smoke from Wildfire and Agricultural Burning on Farmworker Health and Behavior

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Impact of Smoke from Wildfire and Agricultural Burning on
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Abstract

Farmworkers are vulnerable to ambient environmental conditions, and an emerging health hazard is smoke from wildfires and agricultural burning. This smoke poses an immediate threat to the health and wellbeing of farmworkers by increasing the risk of injuries. Additionally, smoke can influence farmers' and farmworkers' decisions about when, where, and how much to work, potentially exacerbating ongoing labor shortages in the agricultural sector. My dissertation quantifies the effect of smoke from 1) wildfires and 2) agricultural burning on farmworker labor and health outcomes.

In the first chapter, we study the effect of wildfire smoke on farmworker labor outcomes in California. Using high-frequency individual-location data, we find that labor declines at both the extensive and intensive margins on days when fields are affected by wildfire smoke. On smoky days, the number of workers in a field is reduced by 17.51% and working hours are reduced by 23.12%, relative to days without smoke. Estimated effects are largest for labor-intensive crops. Farmworkers are more likely to be observed in a field immediately before smoke events and less likely to be observed after. They are also more likely to work in other fields when their primary worksite is treated. Results highlight the significant effects of wildfire smoke on farmworker labor outcomes, showing reductions in work activities and the adoption of substitution behaviors among a marginalized and hard-to-survey group.

In the second chapter, we study the impact of wildfire smoke on workplace injuries among agricultural workers, using workers'-compensation claims between 2007 and 2021. We find a substantial increase in agricultural-worker injuries attributable to wildfire smoke and smoke-induced $PM_{2.5}$. Specifically, a 10 μg/m^3 increase in daily $PM_{2.5}$ exposure from wildfire smoke increases traumatic injuries by 2.3 percent, and exposure to high levels of $PM_{2.5}$ (above 20 μg/m^3) increases traumatic injuries by 14.29 percent relative to days without smoke. The effects of smoke are higher for young workers than for old workers. We find that injuries occur even at levels of $PM_{2.5}$ considered safe. Our back-of-the-envelope calculation suggests that in 2020 alone, wildfire smoke was responsible for approximately 282 additional agricultural-worker injuries in California compared to a hypothetical scenario without smoke.

In the third chapter, using data from the major seven air districts in California engaged in agricultural burning and worker's compensation claims from 2000 to 2021, we investigate the impact of exposure to smoke from agricultural burning on agricultural workers' injuries. Agricultural burning has long been used for various purposes in U.S. agriculture, such as removing crop residue and controlling pests, resulting

in significant emissions of air pollutants. Prior research has mainly focused on its effect on the general population particularly in developing countries. By leveraging daily changes in fire location and wind direction for identification, our findings show that on days with agricultural burnings, there is a 2.6 percent increase in injuries within the downwind zip code. The impact on farmworker injuries is larger when agricultural burnings occur over consecutive days.

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CHAPTER 1

Wildfires and Farmworker Labor

1.1. Introduction

The number and intensity of wildfires are forecast to increase as the climate changes (Abatzoglou and Williams, 2016; NOAA, 2022b). Smoke and particulate matter from wildfires impose large costs on outdoor workers. The costs might be especially large for farmworkers, who may have few margins of adjustment to limit exposure. In this paper, we investigate whether agricultural labor outcomes respond to wildfire smoke at both the extensive margin (whether workers go to work) and the intensive margin (the number of hours worked) using an unbalanced panel of individual-level cell phone location data. By following individuals at fine spatial and temporal scales, we are also able to study novel margins of labor adjustment to wildfires including substitution over time and across space.

This paper contributes to two related literatures. The first is the broad literature quantifying the effect on labor markets of environmental conditions including air pollution (Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015; Hausman et al., 1984), water pollution (Carson et al., 2011), and temperature (Graff Zivin and Neidell, 2014; Neidell et al., 2021). At the macro level, Borgschulte et al. (2022) find that counties exposed to wildfire smoke experience losses in aggregate employment and lower labor force participation during the affected quarter. But research on individual agricultural workers' responses to environmental conditions is limited. Chang et al. (2016) find no evidence that fine particulates affect agricultural labor supply at an indoor pear-packing plant. We add to this literature by focusing on the effects of wildfire smoke on daily labor outcomes for thousands of outdoor farmworkers across thousands of fields.

The second literature studies avoidance behaviors in response to adverse environmental conditions (Barreca et al., 2016; Graff Zivin et al., 2011; Moretti and Neidell, 2011; Ward and Beatty, 2016). While avoidance behavior can mitigate the health effects of harmful environmental conditions, it can be costly; for example, individuals may work fewer hours, choose not to engage in recreational activities, or incur defensive expenditures—see, for example, Graff Zivin and Neidell (2009); He et al. (2022); Ito and Zhang

(2020); Keiser et al. (2018); Moretti and Neidell (2011); Ward and Beatty (2016). By tracking individual farmworkers over days and across fields using individual-level high-frequency cell-phone-location panel data, we are able to document individual-level substitution patterns at fine temporal and spatial scales.

We use novel location and movement data from a company that collects individual-location information from roughly 400 smartphone applications. Each observation consists of a unique device identifier, location information (longitude and latitude), and a time stamp. We join each individual-location observation to statewide field-boundary maps to identify farmworkers and their worksites. To this we add wildfire smoke data from the National Oceanic and Atmospheric Administration's (NOAA's) Hazard Mapping System, data on wildfire-smoke-induced $PM_{2.5}$ from Childs et al. (2022), and weather data from the PRISM Climate Group.

Our research design relies on short-run exogenous variation in smoke from wildfires. Wildfire-induced variation is frequently used to measure the causal impacts of air pollution on a variety of outcomes (Borgschulte et al., 2022; Burke et al., 2022; Chang et al., 2016; Heft-Neal et al., 2023a; Jayachandran, 2009; Miller et al., 2021). Although aggregate temporal variation in air pollution may be the result of economic activity, which affects labor supply and demand decisions, the daily variation in smoke intensity from a wildfire is plausibly exogenous to individual workers. We establish that wildfire smoke plumes as measured by NOAA translate into higher levels of ground-level $PM_{2.5}$. To analyze whether farmworkers go to work less or work fewer hours, we use parsimonious models that include time and location fixed effects. We explore heterogeneous responses to wildfire smoke by comparing farmworkers working more and less labor-intensive crops. We study substitution patterns over time by estimating the number of farmworkers working and the number of hours worked before and after wildfire smoke covers a field. Finally, we look at substitution patterns across space—that is, the degree to which farmworkers are more likely to work in other fields when their usual worksite is affected.

We find that farmworkers work less and, conditional on working, work fewer hours when their worksite is affected by wildfire smoke. These effects are largest for farmworkers working in fields with labor-intensive crops. Farmworkers also seem to exhibit anticipatory behavior: they go to work more and work more hours on days before smoke events. Finally, we find evidence of substitution across space: farmworkers are more likely to change their workplace when smoke affects their usual workplace than when it does not.

The paper proceeds as follows. Section 2 provides background on wildfires and California crop workers. Section 3 presents the data and summary statistics, and it benchmarks our novel cell phone location data against other data on agricultural workers. Section 4 estimates outcomes at the intensive and extensive margins, then examines substitution over time and space. Section 5 discusses the implications of our findings and concludes.

1.2. Background

Wildfires, and the resulting smoke, are salient and recurring natural disasters. In recent decades, the United States has seen more than a doubling in the area burned by wildfires annually (Abatzoglou and Williams, 2016), with California experiencing a disproportionately large increase. The year 2020 was the most destructive in California history, registering 5 of the state's 10 largest wildfires; the largest burned 1,032,648 acres, an area roughly the size of Rhode Island (CalFire, 2022). The number and intensity of wildfires are forecast to increase because of climate change (Jones et al., 2020; NOAA, 2022b). Wildfire smoke is an important contributor to ambient air pollution. In California, wildfire smoke accounted for about half of total $PM_{2.5}$ concentration in recent years, up from less than 20% a decade ago (Burke et al., 2021). The number and size of wildfires increase sharply between May and June and stay high until September.[1]

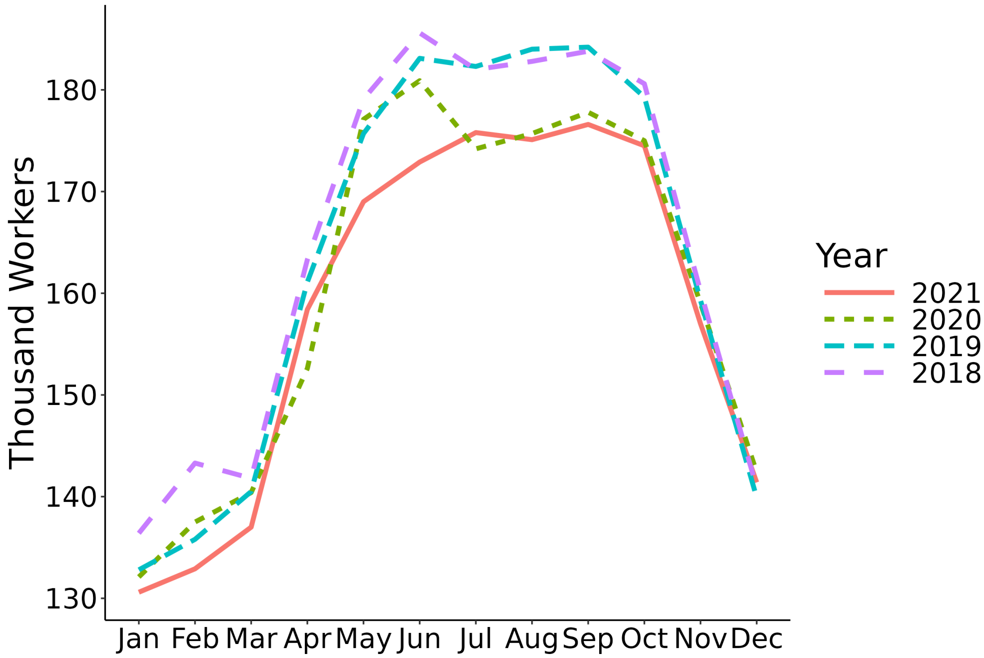
Wildfire smoke exposure can lead to adverse health consequences, notably increased risk of cardiovascular and respiratory illnesses (Black et al., 2017; DeFlorio-Barker et al., 2019; Liu et al., 2017; Reid et al., 2016; Wettstein et al., 2018). Wildfires produce smoke made up of a complex mixture of gases and fine particles that are generated through the combustion of organic materials such as wood. Particulate matter (PM) is a key pollutant of concern from wildfire smoke (EPA, 2021b), particularly fine PM—that is, PM with a diameter of less than 2.5 microns, or $PM_{2.5}$. Research suggests that $PM_{2.5}$ from wildfires may be more hazardous than the same amount from another source. $PM_{2.5}$ from wildfires increases hospitalizations for respiratory illness up to about 10 times more than $PM_{2.5}$ from other sources (Aguilera et al., 2021).

Wildfire smoke also contains other harmful pollutants, including carbon monoxide and air toxins (EPA, 2021b). Carbon monoxide can cause fatigue, dizziness, headaches, and confusion because of inadequate oxygen delivery to the brain (CARB, 2021b). Depending on the materials burned, wildfire smoke can also

[1] Appendix Figure S1.1 highlights these patterns.

contain high levels of toxic metal contaminants, including lead. For example, the California Air Resources Board found dangerous levels of lead in smoke from California's Camp Fire in 2018 (CARB, 2021a).

FIGURE 1.1. Employment of Farmworkers by Month in California



Notes: The lines in the figure show crop-production employment by month in California from 2018 to 2021. The data are retrieved from California's Employment Development Department (EDD, 2020).

Wildfire season coincides with peak employment season for California's agricultural workforce. Figure 1.1 shows farmworker employment by month in California from 2018 to 2021. The number of employed workers sharply increases from April to May, which for most crops is the planting season (USDA, 2010). Employment stays high between May and September, then begins to decline in October. Despite the COVID-19 outbreak in 2020, employment patterns remain largely unchanged from earlier years.

Wildfire smoke likely reduces both the supply of and demand for agricultural labor in a given field on the day of smoke exposure. On the supply side, farmworkers may limit exposure to unhealthy conditions by reducing the amount they choose to work. Farmworkers' ability to adapt their work schedule may lead them to respond differently to adverse environmental conditions compared to other outdoor workers. The likelihood of working during adverse events may depend on various factors. For example, workers who hold H-2A visas may be limited in their ability to choose when and where to work.[2] Only 3% of California employment in crop agriculture in 2020 consisted of H-2A workers, with about 23,925 positions being certified (Martin et al., 2022). However, workers who are family members on family farms or those who have alternative choices for workplaces or employers may have more flexibility.

On the demand side, employers may shift workers' schedules and workplaces to protect worker health and limit potential liability in the event of injury. This behavior may be voluntary or mandatory. Systematic evidence is scarce, but employer surveys suggest that responses to air pollution vary widely. Riden et al. (2020) interview California farmers in 2018 to understand how they respond to air pollution. They find that some farmers remove workers from fields or adjust working hours when air quality is poor but many do not have protocols governing smoke events. In 2019, California implemented the Cal/OSHA outdoor-worker wildfire-protection regulation. When the Air Quality Index is 151 or greater, equivalent to 55.5 μg/m^3 of $PM_{2.5}$, employers must, if feasible, provide an enclosed location where the air is filtered. If this is not feasible or adequate, regulations can require employers to relocate workers to unaffected outdoor worksites, modify work schedules, or reduce work intensity. A priori, the extent to which farmers comply with these regulations is uncertain.

These outcomes occur against a backdrop of chronic agricultural labor shortages in California (BLS, 2020; Charlton et al., 2019; EDD, 2020; Rutledge and Taylor, 2019; USDA, 2021). According to a California Farm Bureau Federation survey in 2019, 56% of farmers reported they had been unable to hire all the employees they would have liked over the past five years (Rutledge et al., 2019). As noted above, wildfires may exacerbate this problem, as wildfire season in California coincides with peak harvest season.

1.3. Data

1.3.1. Worker Data. We use novel cell phone location data to study high-frequency adaptation to environmental conditions. We begin by describing how we create a sample of farmworkers from cell phone location data. We then compare our sample to well-established farmworker data and highlight some of the opportunities and challenges presented by the use of cell phone location data to infer occupation.

[2] When employers face a shortage of domestic farmworkers, they can sponsor immigrants for temporary employment visas. The H-2A temporary agricultural-worker program enables foreign farmworkers to legally work in the United States for sponsoring employers.

Existing data are ill-suited to answering our research questions. Much of what we know about agricultural workers comes from the National Agricultural Workers Survey (NAWS), which interviews farmworkers at their jobsites. Collecting data from a sampling frame of worksites results in a self-selected sample of workers who chose to work on a given day, where selection is driven by environmental conditions. Large social surveys (for example, the Current Population Survey or American Community Survey) that build sampling frames from dwelling units yield small samples because agricultural workers make up a small share of the labor force. In 2019–20, the NAWS sample consisted of 2,172 US crop farmworkers, of whom 905 were located in California (Gold et al., 2021; NAWS, 2022). Finally, most surveys do not offer information about worker behavior over time or at fine timescales, though some survey questions have retrospective components (Gold et al., 2021). As an alternative to surveys, researchers have worked with individual farms or small groups of farms to obtain high-frequency data on worker behavior, but the increased detail may come at the cost of limited external validity (Chang et al., 2016; Hamilton et al., 2021; Hill and Burkhardt, 2021).

We use a sample of cell phone location data from a company that collects individual-location information from roughly 400 mobile applications such as weather apps, messaging apps, free video and file converters, dating apps, and religious and prayer apps. The sample covers California between January 1 and October 11, 2020. Each observation consists of a unique device identifier, location information, time, speed, and horizontal accuracy.[3] The data set is an unbalanced panel in which individuals may be observed multiple times a day but might not be observed every day. The number of observations is time-varying over the sample period, as apps are added and removed from the platform over time. Individuals need not actively use an app to be tracked: tracking functions may be active even if an app is running in the background.

To identify farmworkers, we join cell phone location information to a map of California crop fields. The field-crop map data contain georeferenced data on field boundaries and crops from the California Department of Water Resources, developed by LandIQ (2021). We use the 2018 crop map, the most recent layer publicly available. Using the 2018 field-crop map with 2020 location data introduces a potential source of error if land moved into or out of production between 2018 and 2020. Errors introduced in this way are likely small, as only 1.7% of cropland was converted to other uses between 2012 and 2017 (USDA, 2020).

[3]*Horizontal accuracy* refers to the radius of the margin of the measurement errors. In mobile map applications, the smaller, darker-blue dot represents the latitude and longitude of individuals and the larger, lighter-blue circle shows horizontal accuracy. The lower the horizontal accuracy, the more confidence the mobile device has in the tracked location.

Another source of error is changes in crop type between 2018 and 2020. About 64% of the crop fields in 2016 grew the same crops in 2018. Misclassification is not a large concern, as we only use the crop-type variable to analyze the heterogeneity of workers' responses by labor intensiveness of crop type. Any misclassification of workers between crop-type categories would make estimates more conservative because the resulting differences in response across task intensity would become smaller rather than larger.

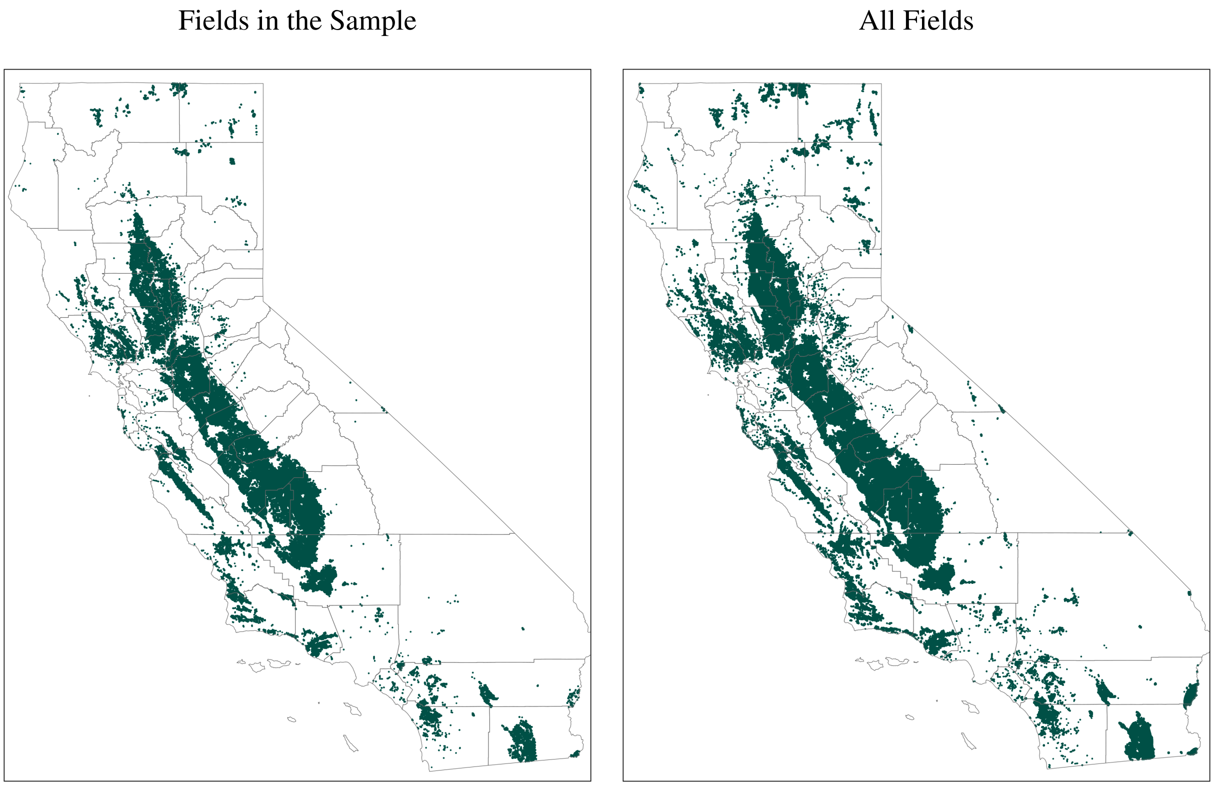
We classify a device as belonging to a farmworker in a given month if it is located within an agricultural field on at least five days during working hours (that is, 6:00 a.m. to 8:00 p.m.) in a month while moving less than or equal to 5 m/s, with horizontal accuracy less than 63 m, which is about the median value in our sample. This definition is ad hoc but reasonable. All results are robust to a host of alternative choices (see appendix 1.6.2.1 for details).

We identify 12,667 farmworkers using the criteria described above. This number represents about 8% of the annual average employment in crop production in California in 2020 and is almost 20 times larger than the sample size of NAWS in 2020 (BLS, 2022; Gold et al., 2021). The farmworkers are selected from a pool of around 3.4 million individuals in the cell phone location data. This means that roughly 0.4% of the individuals in the data are classified as farmworkers, which is consistent with the proportion of crop workers in California's overall population as reported by the Bureau of Labor Statistics and the US Census Bureau (BLS, 2022; USCB, 2022).

Our analysis focuses on fields where farmworkers are observed for at least 10 days during the sample period. We perform robustness checks using alternative criteria, considering fields observed for at least 5, 20, and 30 days, in Table S1.10. However, using more or less balanced samples does not affect our main finding: increased smoke levels reduce the number of workers and average hours worked in a field.

Figure 1.2 maps crop fields in which we observe a worker. We observe at least one worker in about 34.77% of California's crop fields over the sample period. Fields in the sample are evenly spatially distributed across the set of all crop fields in the state. Compared to a map of all fields, we see good geographic coverage, though fields in the relatively remote northeastern part of the state are underrepresented. About 11.5% of farmworkers in the sample are observed in a single field, and 88.5% are observed in more than one field over the course of the sample period.

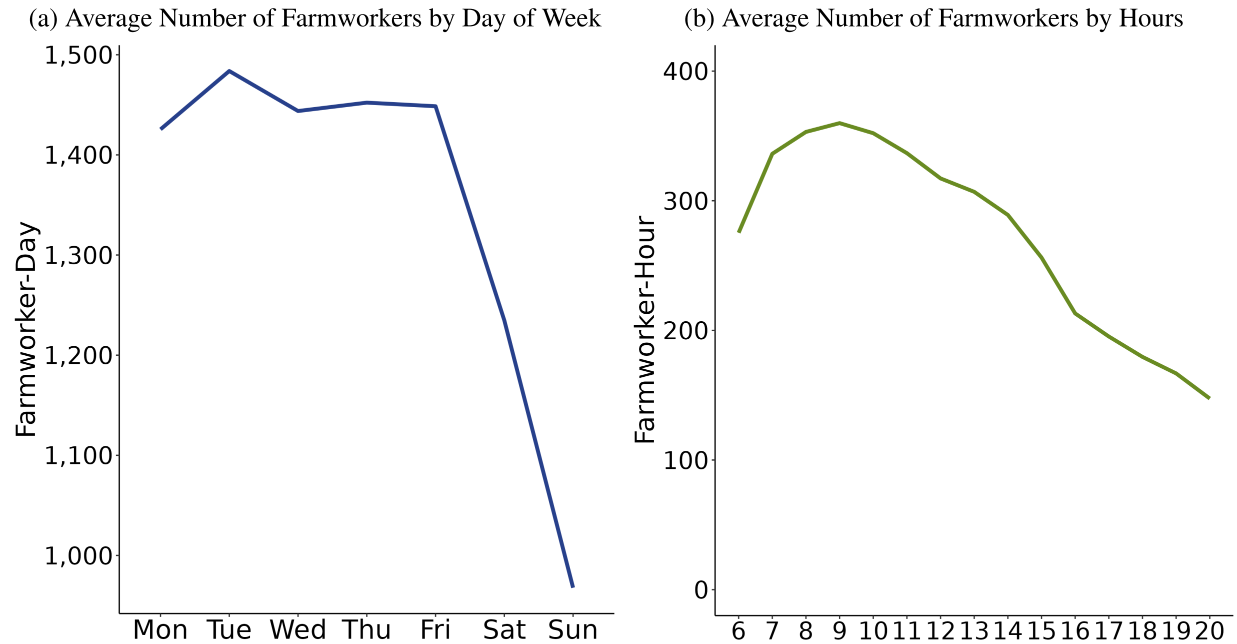
FIGURE 1.2. Fields in the Sample



Notes: The dots in the left panel represent the location of fields in the sample, and the dots in the right panel represent the location of all crop fields in California.

An obvious limitation of our approach is that we infer occupation from location and observe little additional information on the individuals in our sample. As a face-validity check, we compare summary statistics from our sample to statistics on agricultural-crop workers drawn from other sources. Panel (a) in Figure 1.3 shows the daily average number of farmworkers by day of week, and panel (b) shows the daily average number of farmworkers by hour in the sample. Work patterns in our sample are comparable to patterns reported by California farmworkers in NAWS (Gold et al., 2021). NAWS respondents worked an average of 46 hours a week, which matches the statistics of our sample. In panel (b), we see that most farmworkers start to work around 7:00 to 9:00 a.m. and finish their jobs around 4:00 to 6:00 p.m.—about eight or nine hours of work per day. As illustrated in panel (a), farmworkers mostly work Monday to Friday

FIGURE 1.3. Average Number of Farmworkers by Day of Week and Hour



Notes: Panel (a) depicts the daily average number of farmworkers found in fields by day of week. Panel (b) shows the daily average number of farmworkers found in fields by hour.

and more people work on Saturday than Sunday. The implied total number of hours worked per week ranges between 40 and 54, which lines up with survey results from NAWS.

TABLE 1.1. Comparison of the Share of Workers by Crop Type

	Crop Type	Share of EDD	Share of Sample	Share of Sample (hrs)
1	Oilseed and Grain Farming	0.01	0.05	0.04
2	Vegetable and Melon Farming	0.14	0.10	0.14
3	Fruits and Tree Nuts	0.43	0.39	0.37
4	Berry Crops	0.17	0.02	0.04
5	Grapes	0.09	0.15	0.15
6	Citrus Fruits	0.01	0.07	0.05
7	Ornamental Florist and Nursery Products	0.10	0.03	0.04
8	Cotton	0.01	0.01	0.01
9	Other Field Crops	0.04	0.18	0.15

Notes: Column (1) shows the proportion of workers by crop type from California's Employment Development Department (EDD), and column (2) shows the proportion of workers in our sample. Column (3) shows the proportion of hourly observations of workers before aggregating to the daily level. The share of the sample in column (1) is calculated by dividing the monthly average number of employees hired in a certain crop-type category by the monthly average number of total employees from January to October. The shares of the sample in columns (2) and (3) are calculated in the same way.

We consider the representativeness of our sample by comparing the share of workers by crop type to statistics from California's Employment Development Department. Column (1) in Table 1.1 reports the share of workers by crop type from the Employment Development Department, and column (2) reports the proportion of workers observed in a field of each type at least once during a day. Column (3) shows the proportion of hourly observations of workers before aggregating to the daily level. The difference between columns (2) and (3) is that column (3) may better capture work intensity. With the exception of berry crops and the catchall category "other field crops," inferred worker shares are roughly comparable to official department estimates. For example, roughly 40% of the workers identified in our sample work in fruit and tree-nut fields, which matches department data. Some of the differences may be due to classification errors in the underlying field-crop map; for example, other field crops and berries may be difficult to distinguish in the remote-sensing data used to construct the field-crop map.

Figure S1.2 depicts the number of farmworkers tracked by month and the proportion of farmworkers to all individuals in the cell phone location data by month. The number of farmworkers and the ratio of farmworkers to all individuals in the data are consistent over time. This provides some evidence that farmworkers do not select into our sample based on the popularity of specific apps that might be useful for harvest work.

Most farmworkers are observed over the entire length of the sample period. Figure S1.3 shows the distribution of the share of days relative to the entire sample period that farmworkers are observed in our sample. The distribution is left-skewed with a mass at 1, meaning that the majority of farmworkers are observed over the entire sample period.

For each worker, on each day they are observed, we construct a measure of hours worked by subtracting the last time the worker is observed in a field from the earliest time they are found in the same field. Mechanically, this results in an underestimate of hours worked, as the first (last) cell phone pings in a given field likely occur after (before) a worker arrives (departs) for the day. We assign a value of zero to workers who appear only once during a day. The results are robust to excluding these zeros. This introduces measurement error into the outcome variable and introduces noise into our estimates. This is unlikely to bias results but may decrease the precision of our estimates.

We aggregate our sample of farmworkers to the field-by-day level. We count the number of farmworkers observed in each field on each day of our sample period. To compute average hours worked in a field on a day, we average over the number of hours worked for all workers observed in a field. If no workers are observed in a field on a day, the average number of hours worked is set to zero for that field and day. This results in a balanced sample of fields and days, and results are robust to alternative choices described below. To investigate whether individual farmworkers move to fields with cleaner air on days when their usual worksite is affected by wildfire smoke, we work with data at the individual level. This allows us to observe an individual's movement between fields and so cannot be analyzed at the field-by-day level.

TABLE 1.2. Summary Statistics: Dependent Variables

Statistic	Mean	Std Dev	Min	Max	N
Extensive:					
Count	0.113	0.408	0	57	3,941,550
Count (conditional)	1.150	0.708	1	57	386,936
Intensive:					
Average hours worked	0.247	1.343	0.000	14.000	3,941,550
Average hours worked (conditional)	4.138	3.762	0.125	14.000	235,011
Substitution over Space:					
Days with observations	26.588	29.849	1	281	657,813

Notes: The table presents summary statistics of key dependent variables over the period January 1, 2020, to October 11, 2020.

Table 1.2 shows the summary statistics for dependent variables. The average number of workers in a field on a day is 0.113, and conditional on working, 1.15 workers are found in a field. To estimate the effects of smoke on working hours, we calculate the average hours worked for farmworkers in a given field. Conditional on at least one worker observed in a field, the average daily hours worked in that field is 4.138 hours.

When analyzing substitution over space, for each worker and each day, we define a usual worksite as the modal field in which a worker is observed during the previous two weeks.[4] We use location information to determine whether a worker was found at their usual worksite on a given day. We observe workers on roughly 27 distinct working days. According to NAWS, farmworkers work an average of 227 days a year (Gold et al., 2021), which, when scaled for the length of our sample period, works out to about 177 days. This means that we observe approximately one-sixth of the average farmworker's working days.

1.3.2. Wildfire Exposure. To identify smoke-covered areas, we use wildfire smoke data from NOAA's Hazard Mapping System. The data contain information on the area (polygon) covered by smoke plumes from wildfires. NOAA retrieves satellite observations of smoke-plume images in near real-time. Expert image analysts at NOAA process images from satellites into georeferenced polygon data that can be spatially joined to individual fields.[5]

Our primary measure of smoke exposure is an indicator equal to one if any part of a field is covered by a smoke plume at any time during working hours on a day.[6] We extend this by splitting smoke exposure into three densities: light (1–10 μg/m^3), moderate (11–20 μg/m^3), and heavy (above 20 μg/m^3).[7] NOAA reports smoke density in levels: light, medium, and heavy. These measures correspond to smoke concentrations that range between 0 and 10, 10 and 21, and 21 and 32 μg/m^3, respectively. Temporally, if a field experiences any level of smoke during any working hours in a day, we consider it covered with that particular smoke type

[4]The result that the probability of workers working in other fields increases holds for alternative choices of time window within which to assign a farmworker's modal workplace. See appendix 1.6.2.2 for details.

[5]The satellites are GOES-East/West, S-NPP, NOAA-20, Terra, Landsat-7 ETM+, Landsat-8 OLI, and Sentinel-2A/B MSI. Together, these satellites provide a comprehensive image of smoke densities in California (NOAA, 2022a).

[6]The results are robust to alternative choices. The results of robustness checks using different criteria can be found in appendix 1.6.2.3.

[7]Our moderate variable ranges from 11 to 20 for two main reasons. First, in NOAA's original definition, there is overlap between adjacent categories. For instance, a concentration of 10 μg/m^3 could be classified as both light and moderate, making the categories not mutually exclusive. To address this, we opted for a revised categorization with three distinct ranges: 1–10, 11–20, and above 20. In this revised categorization, both the light and moderate categories encompass equal ranges (10 μg/m^3 each), ensuring clearer distinctions between them. Additionally, our smoke variable is derived from original density categories by averaging them throughout the day, which can be considered as a separate measure from the original variable.

and calculate the daily average of all smoke densities on that field. These results remain robust to alternative empirical choices.[8] Subsequently, spatially, if a field is covered by multiple density categories, we select the smoke density that has the largest coverage. For example, if a field has both light- and medium-density smoke, but the area covered by light-density smoke is larger, we classify the field as being covered with light-density smoke. Figure 1.4 depicts the variation of smoke levels on August 19, 2020—three days after the onset of the August Complex fire—and the satellite image of the same day. We include weather data, daily maximum temperature, and daily total precipitation as controls to deal with potential confounding from environmental factors that covary with smoke. The PRISM Climate Group provides daily weather records at a 4×4 km^2 resolution (PRISM, 2021).

We investigate whether atmospheric smoke plumes translate into increased ground-level pollution using a measure of smoke-induced $\text{PM}_{2.5}$. A challenge to obtaining causal estimates of $\text{PM}_{2.5}$ attributable to wildfire smoke is that much of the cross-sectional variation in $\text{PM}_{2.5}$ is due to sources other than wildfires, such as nearby roads and factories. To address this challenge, we use a measure of $\text{PM}_{2.5}$ exposure attributable to wildfire smoke constructed by Childs et al. (2022). This measure has been extensively validated and used in previous work, studying the impacts of $\text{PM}_{2.5}$ from wildfires on health outcomes (Heft-Neal et al., 2023c), educational outcomes (Wen and Burke, 2022), and behavioral changes (Burke et al., 2022).

Variable construction proceeds as follows. Initially, Childs et al. (2022) compute $\text{PM}_{2.5}$ anomalies by measuring deviations from median values on days without smoke for each monitor:

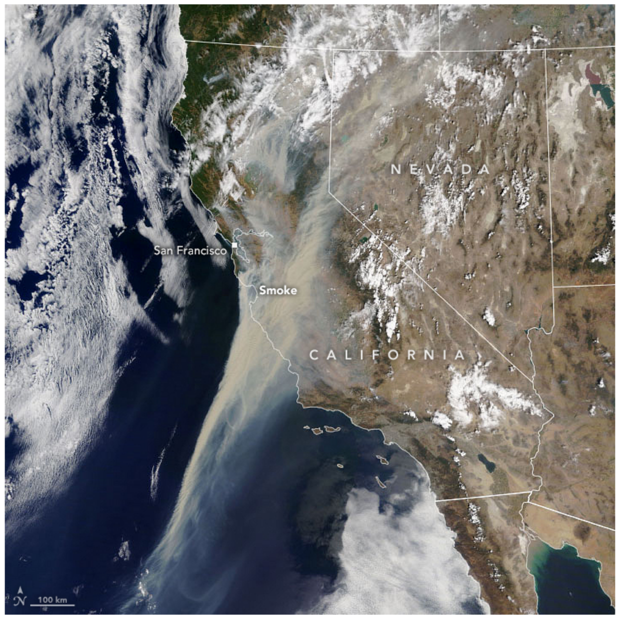
$$\widetilde{\text{PM}}_{idmy} = \text{PM}_{idmy} - \overline{\text{PM}}^{\text{NS}}_{imy}$$

Here, PM_{idmy} represents the $\text{PM}_{2.5}$ concentration at station i on day d in month m and year y, and $\overline{\text{PM}}^{\text{NS}}_{imy}$ indicates the median $\text{PM}_{2.5}$ in station i and month m within a three-year window, including y, when no smoke was present. PM_{idmy} is calculated using daily average concentrations from EPA monitoring stations. To calculate $\overline{\text{PM}}^{\text{NS}}_{imy}$, smoke days are identified using data on smoke plumes from NOAA Hazard Mapping System and simulated air trajectories from smoke-producing fire points detected by Hazard Mapping System using the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model.

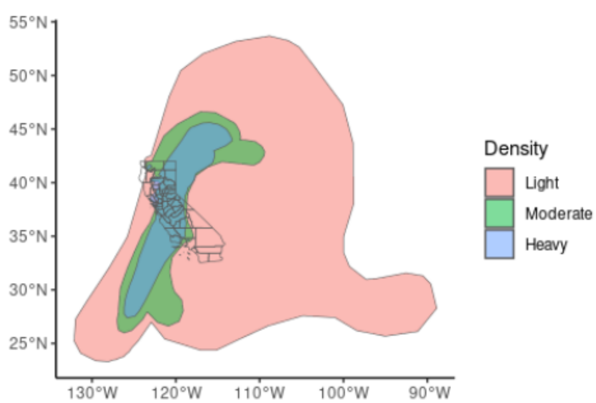
[8] See appendix 1.6.2.4 for alternative smoke-cover measures.

FIGURE 1.4. Satellite Image and NOAA Smoke Polygon

(a) Satellite Image of Smoke



(b) NOAA Smoke Polygon



Notes: Panel (a) shows an image from NASA's Terra satellite from August 19, 2020, three days after the onset of the August Complex fire (NASA, 2020), and panel (b) shows NOAA's smoke-polygon image from the same day.

Finally, to construct a measure of smoke-induced abnormal $PM_{2.5}$, SmokePM_{idmy}, $\widetilde{\text{PM}}_{idmy}$ is multiplied by smoke $_{\text{idmy}}$, where $\text{smoke}_{\text{idmy}} = 1$ if there was smoke over location i, as follows:

$$\text{SmokePM}_{idmy} = \max\left(\widetilde{\text{PM}}_{idmy} \times \text{smoke}_{idmy}, 0\right)$$

Given the temporally and spatially limited and time-varying number of monitoring stations, a statistical model is employed to capture the local and temporal variation of wildfire-induced smoke. Childs et al. (2022) generate a SmokePM grid using SmokePM $_{idmy}$ with a spatial resolution of 10×10 km^2 using machine-learning techniques with various data such as weather, fire (from the Hazard Mapping System), and elevation. We aggregate SmokePM grids at the field level by averaging values within each field and day, providing a field-specific measure of smoke-$PM_{2.5}$ concentration.

To ensure that we measure the impact of wildfire smoke rather than just proximity to wildfires, we use Hazard Mapping System active-fire data, which provide the location of active fires. We calculate the distance from the center of each field to the nearest fire center point and categorize it into one of four groups based on 20 km increments: less than or equal to 20 km, 20 to 40 km, 40 to 60 km, and more than 60 km.

TABLE 1.3. Summary Statistics: Exploratory Variables

Statistic	Mean	Std Dev	Min	Max	N	Share of Obs
Smoke:						
Smoke	0.215	0.410	0	1	3,941,550	
Light	5.000	0.000	5	5	255,218	0.065
Moderate	14.315	2.535	10.500	16.000	589,695	0.150
Heavy	24.447	2.745	21.500	27.000	629	0.0002
$PM_{2.5}$:						
$PM_{2.5}$	5.809	16.854	0.000	295.904	3,941,550	
Low	7.570	5.671	0.003	20.000	465,191	0.118
Moderate	28.664	5.626	20.000	40.000	168,943	0.043
High	68.757	23.225	40.001	295.904	183,369	0.047
Weather:						
Max temperature (°F)	78.655	14.953	27.269	119.692	3,941,550	
Precipitation (mm)	0.524	2.745	0.000	99.830	3,941,550	

Notes: The table presents summary statistics of key independent variables over the period January 1, 2020, to October 11, 2020. "Max Temperature" denotes the daily maximum temperature, and "Precipitation" is the daily total precipitation of a field. "Share of Obs" indicates the share of observations of a variable over the total number of observations in the sample.

Table 1.3 presents summary statistics for our exposure measures and captures the scale of the 2020 wildfire season. Within our sample, 21.5% of field-days were exposed to smoky conditions. Smoke exposure can be further decomposed by density, with 6.5% of fields experiencing light, 15% moderate, and 0.02% heavy smoke density. The average $PM_{2.5}$ level attributable to wildfire smoke is approximately 6 μg/m^3.

We divide $PM_{2.5}$ levels into three categories to estimate nonlinear relationships between $PM_{2.5}$ and labor outcomes. *Low* is defined as 0 μg/m^3 < $PM_{2.5}$ ≤ 20 μg/m^3, *moderate* as 20 μg/m^3 < $PM_{2.5}$ ≤ 40 μg/m^3, and *high* as above 40 μg/m^3. Among field-days, 11.8% experienced low $PM_{2.5}$ levels, 4.3% moderate, and 4.7% high.

To estimate the relationship between wildfire smoke and labor, we join farmworker-location data to actual and potential wildfire smoke exposure. We construct a balanced panel of fields from LandIQ for every day between January 1 and October 11, 2020 (the period in which we observe worker movement). We join our measures of wildfire smoke, $PM_{2.5}$, weather, and fire location to each field. To construct the outcome variable of interest, if a farmworker was in a given field on a given day, we merge location and movement data with field boundaries delineated by LandIQ. From this, we can construct measures of exposure or avoided exposure.

1.3.2.1. *Smoke and $PM_{2.5}$.* One reasonable question that arises is whether smoke plumes measured by satellite imagery can capture ground-level air pollution. While various pollutants associated with smoke influence labor outcomes, we focus on the relationship between smoke and $PM_{2.5}$, a major public health concern (EPA, 2021b). We estimate the following relationship between smoke and $PM_{2.5}$:

$$\mathrm{PM}_{\mathrm{f,d}} = \alpha_1 \,\mathrm{Smoke}_{\mathrm{f,d}} + \mathbf{W}_{\mathrm{f,d}}\,\Pi + \mathrm{fire}_{\mathrm{f,d}}\,\Theta + \delta_{fw} + \gamma_t + \epsilon_{f,d} \tag{1.1}$$

Here, $\mathrm{PM}_{f,d}$ indicates the level of $PM_{2.5}$ attributed to smoke in field f on day d. $\mathrm{Smoke}_{\mathrm{f,d}}$ is a binary variable equal to 1 when field f at date d is covered with wildfire smoke and 0 otherwise. We include a rich set of controls: $\mathbf{W}_{f,d}$ denotes a vector of weather variables, including the daily maximum temperature divided into five categories, each separated by 20°F increments, ranging from less than 40°F to greater than 100°F. Additionally, $\mathbf{W}_{f,d}$ incorporates other weather variables such as total precipitation and precipitation squared. In addition to these controls, we include other variables: $\mathrm{fire}_{f,d}$ is the distance from the center of each field to the nearest fire center point in four bins; δ_{fw} denotes field × week-of-the-year fixed effects, and γ_t denotes weekend fixed effects. Because we only have data on labor decisions for a relatively short period of less than one year, we do not use day-fixed effects.

TABLE 1.4. Smoke and $PM_{2.5}$

	(1)	(2)	(3)	(4)	(5)
Smoke	23.93***	6.748***	5.487***	5.353***	5.171***
	(2.611)	(0.9051)	(0.7304)	(0.7259)	(0.6970)
Dep. var. mean	5.321	5.321	5.321	5.321	5.321
Observations	3,941,550	3,941,550	3,941,550	3,941,550	3,941,550
R^2	0.39751	0.69331	0.83057	0.83135	0.81015
Weather and fire Controls	✓	✓	✓	✓	✓
Week fixed effects		✓			
Field-by-week fixed effects			✓	✓	
Weekend fixed effects				✓	✓
County-by-week fixed effects					✓

Notes: The table shows the relationship between $PM_{2.5}$ and Smoke, where Smoke is equal to 1 if a field is covered by any smoke in a day and 0 otherwise. Standard errors are two-way clustered by field and date
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 1.4 presents the results. We observe that when a field is covered by smoke, $PM_{2.5}$ increases by approximately 5.353 μg/m^3 as shown in column (4). This number is close to the result reported by Childs et al. (2022). They find that when a smoke plume is present overhead, $PM_{2.5}$ concentrations increase by an average of 4.5 μg/m^3 once they control for average $PM_{2.5}$ differences across monitors, states, months, and years.

Notably, SmokePM_{idmy} is constructed using smoke data, potentially introducing a mechanical relationship between the two variables, which needs to be considered when interpreting the results. When $\widetilde{\text{PM}}_{idmy}$ is positive but $\text{smoke}_{idmy} = 0$, or when $\widetilde{\text{PM}}_{idmy} = 0$ but smoke_{idmy} is positive, multiplying these variables will result in $\text{SmokePM}_{idmy} = 0$. This may strengthen the association between SmokePM_{idmy} and the smoke variable compared to simply regressing ground-level $PM_{2.5}$ on smoke. However, apart from these cases, using SmokePM_{idmy} is less likely to pose issues when estimating equation 1.1.

In our main analyses, we investigate the impact of smoke on labor outcomes rather than estimating the effects of $PM_{2.5}$. We choose smoke density as our main variable of interest because wildfire smoke includes a host of pollutants, such as carbon monoxide, nitrogen oxides, ozone precursors (in the form of various volatile organic compounds) (CDC, 2022), and lead (CARB, 2021a), all of which could influence labor outcomes over and above fine particulates. However, as a robustness check, we reestimate our main regression equations using exposure to wildfire-induced $PM_{2.5}$ as a treatment variable.

1.4. Research Design and Results

We now describe the identifying variation and empirical approach used to estimate the effect of wildfire smoke on farm labor outcomes. We begin with the extensive margin: do workers turn up at a worksite on days when it is affected by smoke? We then turn to the intensive margin: do the workers who turn up at an affected field work fewer hours?

To identify the causal impact of smoke exposure, we use plausibly exogenous variation in wildfire smoke, as measured by smoke plumes. The key empirical challenge for studies that measure the causal effect of air pollution on labor market outcomes is isolating pollution variation that is not a function of factors that directly drive economic activity (Borgschulte et al., 2022). By using daily variation in wildfire smoke, we sidestep issues related to the joint determination of economic activity and air quality. Wind disperses wildfire smoke over thousands of miles, yielding plausibly exogenous variation in smoke that is unconnected to factors that affect underlying economic conditions.

1.4.1. Extensive Margin.

1.4.1.1. *Main Results.* We begin our analyses by considering workers' responses to wildfires at the extensive margin. We regress the number of workers in a field on two measures of smoke exposure—a binary treatment and three mutually exclusive categories that capture different levels of smoke—mirroring NOAA's categories. Formally, we estimate the following models:

$$\mathrm{Workers}_{\mathrm{f,d}} = \alpha_1\,\mathrm{Smoke}_{\mathrm{f,d}} + \mathbf{W}_{\mathrm{f,d}}\,\Pi + \mathrm{fire}_{\mathrm{f,d}}\,\Theta + \delta_{fw} + \gamma_t + \epsilon_{f,d} \tag{1.2}$$

$$\mathrm{Workers}_{\mathrm{f,d}} = \beta_1\,\mathrm{Light}_{\mathrm{f,d}} + \beta_2\,\mathrm{Moderate}_{\mathrm{f,d}} + \beta_3\,\mathrm{Heavy}_{\mathrm{f,d}} + \mathbf{W}_{\mathrm{f,d}}\,\Pi + \mathrm{fire}_{\mathrm{f,d}}\,\Theta + \delta_{fw} + \gamma_t + \epsilon_{f,d}, \tag{1.3}$$

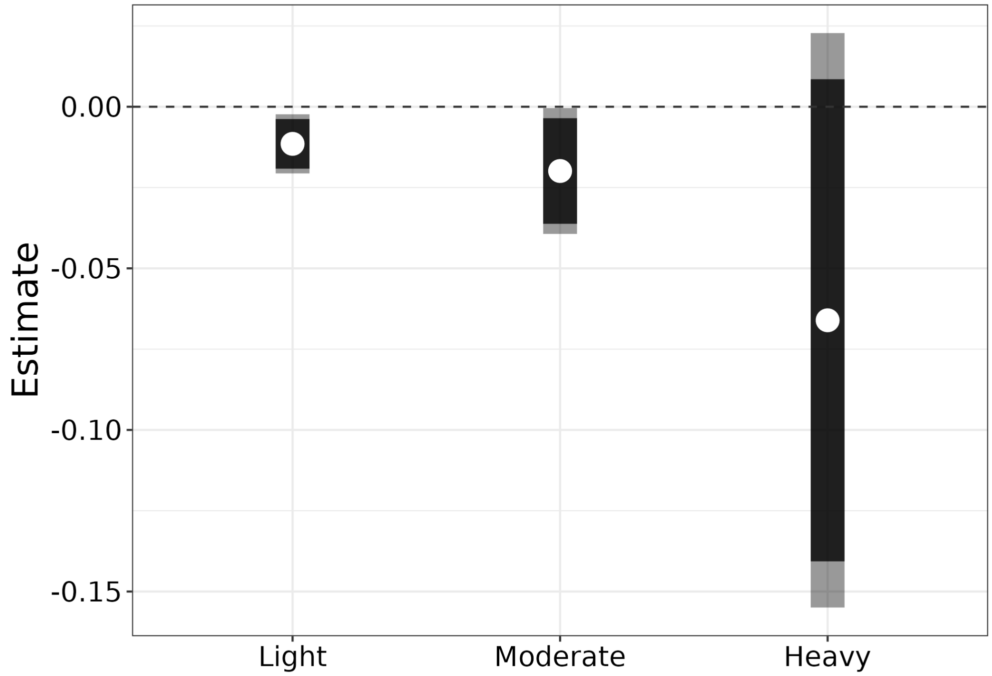
Here, $\mathrm{Workers}_{f,d}$ is the total number of workers observed in field f on day d. $\mathrm{Smoke}_{\mathrm{f,d}}$ is a binary variable that takes on the value of 0 or 1, indicating the absence or presence of wildfire smoke in a field at location f on date d. We extend the analysis by breaking $\mathrm{Smoke}_{\mathrm{f,d}}$ into three mutually exclusive categories—$\mathrm{Light}_{\mathrm{f,d}}$, $\mathrm{Moderate}_{\mathrm{f,d}}$, and $\mathrm{Heavy}_{\mathrm{f,d}}$—that indicate smoke density. As a robustness check, we conduct additional analyses that include county-by-week fixed effects and present the results in appendix 1.6.3. Standard errors are two-way clustered by field and date to account for correlated adaptive behavior within field and date.

TABLE 1.5. Extensive and Intensive Margin

(A) Extensive	(1)	(2)	(3)	(4)	(5)
Smoke	0.1227***	-0.0145**	-0.0186**	-0.0138**	-0.0126**
	(0.0108)	(0.0068)	(0.0076)	(0.0054)	(0.0049)
Dep. var. mean	0.1129	0.1129	0.1129	0.1129	0.1129
Control. mean	0.0788	0.0788	0.0788	0.0788	0.0788
Observations	3,941,550	3,941,550	3,941,550	3,941,550	3,941,550
R^2	0.03306	0.06691	0.60135	0.60297	0.07607
(B) Intensive					
Smoke	0.2724***	-0.0440***	-0.0506***	-0.0400***	-0.0350***
	(0.0243)	(0.0151)	(0.0171)	(0.0124)	(0.0113)
Dep. var. mean	0.2467	0.2467	0.2467	0.2467	0.2467
Control. mean	0.1730	0.1730	0.1730	0.1730	0.1730
Observations	3,941,550	3,941,550	3,941,550	3,941,550	3,941,550
R^2	0.01380	0.02889	0.52838	0.52911	0.03379
Weather and fire Controls	✓	✓	✓	✓	✓
Week fixed effects		✓			
Field-by-week fixed effects			✓	✓	
Weekend fixed effects				✓	✓
County-by-week fixed effects					✓

Notes: Panel (A) displays the results of the extensive-margin analyses obtained using regression equation 1.2, while panel (B) presents the results of the intensive-margin analyses obtained using regression equation 1.4. Standard errors are two-way clustered by field and date.

FIGURE 1.5. Extensive Margin



Notes: The plotted coefficients (the dots in the middle) are obtained from a regression of equation 1.3. The bottom labels refer to three levels of smoke density. Dark lines show their 90% and 95% confidence intervals. All regressions include field × week and weekend fixed effects, daily-maximum-temperature bins, and controls for precipitation, precipitation squared, and distance to fire. Standard errors are two-way clustered by field and date.

We find evidence that farmworker labor responds to wildfire smoke at the extensive margin. Panel (A) in Table 1.5 reports estimates from regression equation 1.2, while Figure 1.5 and appendix Table S1.3 provide estimates of regression equation 1.3. The presence of wildfire smoke significantly reduces the number of farmworkers working in a field. On days when a field is exposed to wildfire smoke, the number of farmworkers working in fields decreases by 17.51%, a statistically significant reduction relative to a smoke-free day. Further, wildfire smoke's impact is increasing in its density, with a 14.59% reduction in the number of farmworkers in fields affected by light smoke plumes and a 25.25% decrease in fields with moderate plumes compared to normal days. For heavy-smoke days, we find imprecise estimates of a large effect. While the point estimate is the largest across all categories, it is not statistically significant. This is likely because only 0.02% of field-days are exposed to heavy smoke as defined by NOAA.

1.4.1.2. *Heterogeneity by Task.* We now investigate heterogeneity in response to wildfire smoke at the extensive margin. Is the effect of wildfire smoke larger for farmworkers working with more labor-intensive crops? Following Sumner (2021), we divide the fields into two groups based on whether they grow more or less labor-intensive crops. We classify crops as labor-intensive when the hired-labor shares of operating and total costs are high. For our purposes, crop fields that contain apples, lettuce, leafy greens, cherries, grapes, peaches and nectarines, peppers, strawberries, and bush berries are deemed labor-intensive. All other crop fields are classified as less labor-intensive.

TABLE 1.6. Extensive Margin: More Labor Intensive vs. Less Labor Intensive

(A) Labor Intensive	(1)	(2)	(3)	(4)	(5)
Smoke	0.1070***	-0.0132	-0.0265***	-0.0203***	-0.0191***
	(0.0106)	(0.0093)	(0.0100)	(0.0071)	(0.0066)
Dep. var. mean	0.0935	0.0935	0.0935	0.0935	0.0935
Control. mean	0.0652	0.0652	0.0652	0.0652	0.0652
Observations	1,047,660	1,047,660	1,047,660	1,047,660	1,047,660
R^2	0.03620	0.08005	0.47243	0.47567	0.09365
(B) Less Labor Intensive					
Smoke	0.1287***	-0.0151**	-0.0160**	-0.0116**	-0.0103**
	(0.0113)	(0.0062)	(0.0069)	(0.0050)	(0.0045)
Dep. var. mean	0.1199	0.1199	0.1199	0.1199	0.1199
Control. mean	0.0837	0.0837	0.0837	0.0837	0.0837
Observations	2,893,890	2,893,890	2,893,890	2,893,890	2,893,890
R^2	0.03244	0.06480	0.62744	0.62875	0.07422
Weather and fire Controls	✓	✓	✓	✓	✓
Week fixed effects		✓			
Field-by-week fixed effects			✓	✓	
Weekend fixed effects				✓	✓
County-by-week fixed effects					✓

Table 1.6 presents the results of the extensive-margin analysis separated by task intensity. We find evidence that farmworkers working in more labor-intensive crop fields work less than farmworkers in less labor-intensive crop fields when their fields are exposed to wildfire smoke. Specifically, the number of workers in labor-intensive crop fields decreases by 31.13%, whereas in less labor-intensive crop fields the reduction is 13.86%. The reduction in the labor force for labor-intensive fields is nearly double that observed in less labor-intensive fields.

Note that some caution is required when interpreting these results as solely stemming from the more or less labor-intensive nature of the crop. Other aspects of production may also play a role. For instance, less labor-intensive crops often involve increased mechanization, which may reduce exposure. For example, tomato harvesters, who operate from within enclosed cabs, can be somewhat protected from smoke.

1.4.2. Intensive Margin: Hours Worked. We now turn to the effect of wildfire smoke on the number of hours worked. We estimate models that are symmetric to those used to study the extensive margin, except we regress the average hours worked by all workers observed in a field on our measures of wildfire smoke exposure and other controls.

Formally, we estimate the following models:

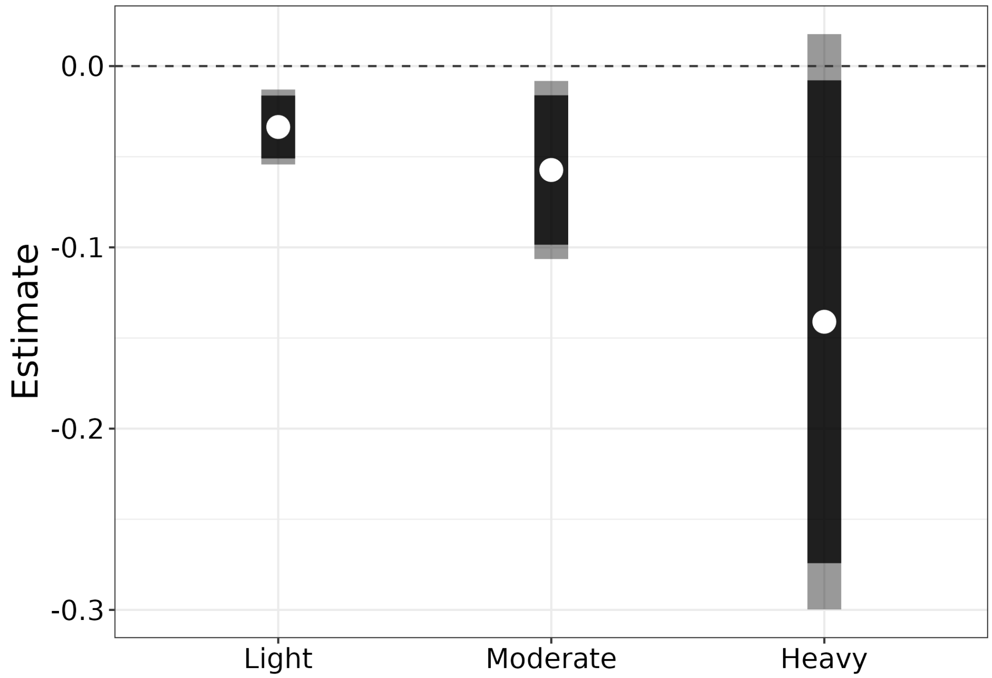
$$\text{Hours Worked}_{f,d} = \alpha_1\,\text{Smoke}_{\text{f,d}} + \mathbf{W}_{\text{f,d}}\,\Pi + \text{fire}_{\text{f,d}}\,\Theta + \delta_{fw} + \gamma_t + \epsilon_{f,d} \tag{1.4}$$

$$\text{Hours Worked}_{f,d} = \beta_1\,\text{Light}_{\text{f,d}} + \beta_2\,\text{Moderate}_{\text{f,d}} + \beta_3\,\text{Heavy}_{\text{f,d}} + \mathbf{W}_{\text{f,d}}\,\Pi + \text{fire}_{\text{f,d}}\,\Theta + \delta_{fw} + \gamma_t + \epsilon_{f,d} \tag{1.5}$$

Here, Hours Worked$_{f,d}$ is the average working hours of all workers in field f on day d. For instance, suppose worker A and worker B are present in a field. If worker A works for two hours and worker B four hours on the field in a given day, then the average work hours for the field on that particular day, denoted as Hours Worked$_{f,d}$, is three. Recall that we infer the number of hours worked in a field by looking at the difference in time between the first and the last time a farmworker is in a field in a given day. If there is no one present in a field or if all farmworkers in the field are observed only once in a day, Hours Worked$_{f,d}$, the average number of hours worked by all workers in that field in a given day, is set to 0. Other control variables and fixed effects are defined as above (equations 1.1, 1.2 and 1.3).

We find that, on average, farmworkers work fewer hours on smoky days. Estimates from specification 1.4 are shown in panel (B) of Table 1.5 and those from specification 1.5 in Figure 1.6; complete results are reported in appendix Table S1.4. Interpreting our preferred specification, which includes field-by-week and weekend fixed effects in column (4) in Table 1.5, we observe that the average number of working hours of workers in a field is reduced by 23.12% relative to smoke-free days. When we examine estimates based on varying levels of smoke density in Figure 1.6 and appendix Table S1.4, working hours are about 19.42% lower in fields with light smoke and 33.12% lower in fields with moderate smoke. Again,

FIGURE 1.6. Intensive Margin



Notes: The plotted coefficients, represented by dots in the middle, show the marginal effects of wildfire smoke on working hours. The bottom labels refer to three levels of smoke density. Dark lines show the estimates' 90% and 95% confidence intervals. All regressions include field × week and weekend fixed effects, daily-maximum-temperature bins, and controls for precipitation, precipitation squared, and distance to fire. Standard errors are two-way clustered by field and date.

the point estimates are largest on heavy-smoke days, with an 81.5% reduction in working hours compared to smoke-free days, but this estimate is imprecise because only a handful of field-day observations occur on a heavy-smoke day.

Last, we explore heterogeneity by labor intensity in the intensive-margin response and present results in appendix Table S1.5. We find that the average number of hours worked by workers in labor-intensive crop fields tends to decline more than the hours worked by workers in less labor-intensive crop fields. Specifically, the percentage reduction in hours worked for labor-intensive crop fields is approximately 1.7 times greater than that for less labor-intensive crop fields.

The point estimates translate into about an hour reduction in time spent in a field if we do a calculation using the average hours worked, about 4.2 hours. To provide some perspective on the estimated magnitude, we compare it with results from a study on temperature and labor. Graff Zivin and Neidell (2014) use American Time Use Surveys to investigate the impact of high temperatures on outdoor workers, including agricultural laborers. They find that on days with temperatures exceeding 100°F, these workers reduce their working hours by nearly one hour compared to days with more moderate temperatures. The working-hour reductions observed among farmworkers in our sample during wildfire smoke events are nearly identical to the finding of Graff Zivin and Neidell (2014).

We do not fully capture various types of farmworker's adaptation to smoke, including wearing respirators and masks[9]. But suppose we assume that estimated magnitudes of reductions in work activities represent individual adaptation levels to different levels of smoke. In that case, observed reductions in labor outcomes at both the intensive and extensive margins seem small from a public health perspective. Even at low levels, exposure to smoke poses significant health risks, as evidenced by a growing literature indicating that even minor exposure to $PM_{2.5}$ over short or prolonged periods can elevate the risk of illnesses and mortality (Di et al., 2017; Miller et al., 2021). This risk is particularly pronounced for individuals exposed to smoke from wildfires (Aguilera et al., 2021). However, if we also consider the broader economic effects of smoke rather than solely focusing on public health, we may find offsetting benefits on days with smoke, such as higher wages due to increased labor demand. These factors can jointly affect the net welfare effects of smoke on farmworker labor.

1.4.3. Substitution across Time and Space. Given that fewer workers are observed in smoke-affected fields, and the average number of hours worked (among those who work) declines, we now explore other dimensions of adaptation to wildfire smoke that workers and farmers may use to compensate for lost time. Our rich individual-level data set allows us to explore substitution patterns across time and space. First, we ask whether we observe more (or fewer) workers in fields in the days leading up to or following a wildfire event. Parallel to our main analysis, we then ask whether workers are observed for longer (or shorter) periods in the days leading up to or following an event. Last, we explore whether we observe workers in other fields when their primary worksite is experiencing a smoke event.

1.4.3.1. *Substitution over Time.* By consulting publicly available forecasts, farmworkers or employers can reasonably anticipate that their worksite may be smoke-affected. In response, farmworkers may work more before a potential smoke event in anticipation of lost work. Following a smoke-impacted day on their field, workers may be less likely to be observed, as smoke-impacted fields could temporarily halt their operation or workers could suffer from smoke-induced health issues. To the extent that workers can

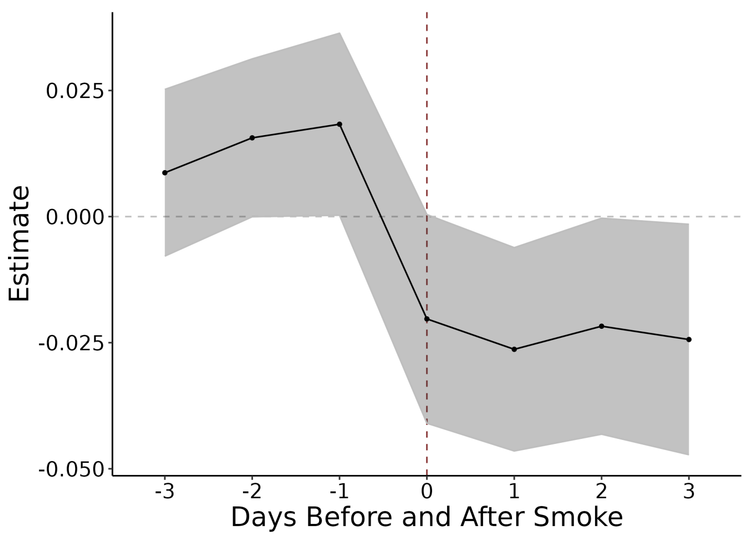
[9]Conversations with farmers and public health advocates suggest that the use of N-95 respirators is rare in the field.

substitute over time, the net effect of wildfire smoke will be smaller or larger than the contemporaneous estimates presented above. To investigate whether workers substitute across time, we extend the extensive- and intensive-margin analysis above as follows:

$$\mathrm{Y_{f,d}} = \sum_{j=-3}^{3} \pi_j \mathbf{1}\left(\tau_{f,d} = j\right) + \mathbf{W}_{\mathrm{f,d}}\,\Pi + \mathrm{fire_{f,d}}\,\Theta + \delta_{fw} + \gamma_t + \epsilon_{f,d} \tag{1.6}$$

Here, an event is defined as a day when a field is covered with any level of smoke. $\tau_{f,d}$ denotes the event date, $\tau \leq -1$ denotes $|j|$ days before the event, and $\tau \geq 1$ denotes j days after the event. For example, the event date is defined such that if $j = -1$, $\tau = 1$ if a field f is covered with any level of smoke the following day and $\tau = 0$ otherwise. The coefficients should be interpreted relative to an average day, which is defined as 4 to 7 days before and 4 to 7 days after the smoke event date.

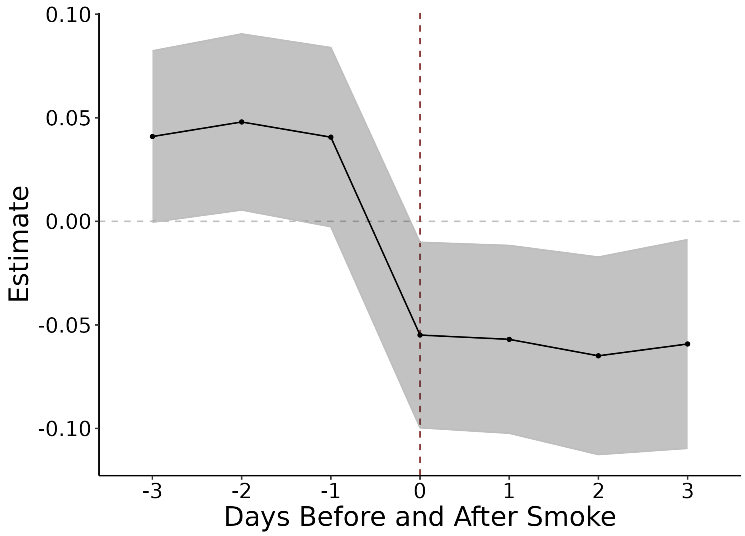
FIGURE 1.7. Substitution over Time: Extensive Margin



Notes: The figure depicts the number of workers working in field before and after a smoke event, relative to normal days. Gray areas show the estimates' 95% confidence intervals. All regressions include field × week and weekend fixed effects, daily-maximum-temperature bins, and controls for precipitation, precipitation squared, and distance to fire. Standard errors are two-way clustered by field and date.

Figure 1.7 and Table S1.6 reports extensive-margin estimates from equation 1.6. We find evidence that farmworkers or farmers anticipate smoke events, and we observe more workers in a field on days before an expected smoke event relative to the days outside of the window from three days before the event date to

FIGURE 1.8. Substitution over Time: Intensive Margin



Notes: The plotted coefficients, represented by black dots, show the marginal effects of wildfire smoke on working hours before and after the smoke event, relative to normal days. Gray areas show the estimates' 95% confidence intervals. All regressions include field × week and weekend fixed effects, daily-maximum-temperature bins, and controls for precipitation, precipitation squared, and distance to fire. Standard errors are two-way clustered by field and date.

three days after. On one day before a smoke event, the number of workers working in fields increases by 10.29%. After smoke-impacted days, farmworkers are less likely to work. Farmworkers are about 12.20%–14.78% less likely to work than usual.

Next, we look at whether workers adjust working hours across days in anticipation of, or in response to, a wildfire smoke event. The results are presented in Figure 1.8 and appendix Table S1.7. We find evidence that farmworkers work more hours than usual in the days leading up to a smoke event and less after the smoke event as we find for extensive margin analysis.

Both supply- and demand-side factors can contribute to the reduction in working days and hours after smoky days. Workers may work less after the smoky days because smoke-impacted farms temporarily cease operations (Gross, 2021) or because workers experience health problems that last for several days. Beatty and Lee (2023) find that smoke increases the risk of farmworker injuries on smoky days in California. According to Heft-Neal et al. (2023a), there is a 30%–110% increase in emergency department visits for asthma, chronic obstructive pulmonary disease, and cough during the week following a day of extreme smoke.

1.4.3.2. *Substitution across Space.* In contrast to the analysis above, we analyze substitution across space at the level of the individual farmworker. This allows us to track the same worker across fields. For each week, we define a worker's worksite as the modal field in which they are observed over the previous two weeks. We choose a two-week window, as opposed to, say, the entire sample period, as farmworkers are often temporary hires, may work in different fields over the growing season, and may only work for a few weeks during the harvest season.[10] We present the alternative choices about a worker's usual worksite in appendix Table S1.1. The coefficients should be interpreted as the change in the probability of switching to other fields.

To explore the possibility that workers substitute across space, we estimate the following linear probability model:

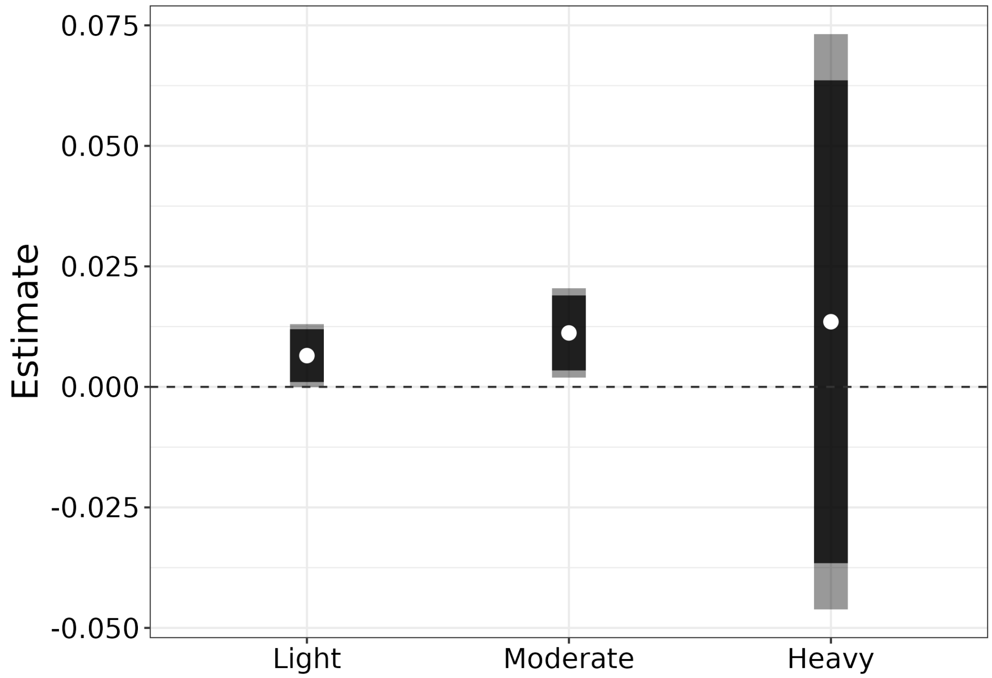
$$\text{Change}_{\text{i,d}} = \beta_1\,\text{Smoke}_{\text{f,d}} + \mathbf{W}_{\text{f,d}}\,\Pi + \text{fire}_{\text{f,d}}\,\Theta + \delta_{fw} + \gamma_t + \rho_i + \epsilon_{f,d} \tag{1.7}$$

$$\text{Change}_{\text{f,d}} = \beta_1\,\text{Light}_{\text{f,d}} + \beta_2\,\text{Moderate}_{\text{f,d}} + \beta_3\,\text{Heavy}_{\text{f,d}} + \mathbf{W}_{\text{f,d}}\,\Pi + \text{fire}_{\text{f,d}}\,\Theta + \delta_{fw} + \gamma_t + \rho_i + \epsilon_{f,d} \tag{1.8}$$

Here, $\text{Change}_{\text{i,d}}$ is a binary variable equal to 1 if a farmworker switches to another field when their usual field is covered with smoke and 0 otherwise. i indexes farmworkers, f indexes usual fields, and d indexes days. We include the set of fixed effects used in the field-level extensive- and intensive-margin analyses, with the additional inclusion of individual fixed effects denoted as ρ_i.

[10]For the first and second weeks of the sample, we identify the typical field based on the first week's observations, as we do not have information on where farmworkers were in the previous two weeks.

FIGURE 1.9. Substitution across Space



Notes: The plotted coefficients (the dots in the middle) are obtained from a linear probability model regression of the probability that a farmworker moves to other fields when their usual field is covered with smoke (equation 1.8). The bottom labels refer to three levels of smoke density. Dark lines show the estimates' 90% and 95% confidence intervals. All regressions include individual, field × week, and weekend fixed effects, daily-maximum-temperature bins, and controls for precipitation, precipitation squared, and distance to fire. Standard errors are two-way clustered by field and date.

We find that workers substitute away from affected fields. Specifically, when their regular workplace is affected by smoke, the likelihood of farmworkers switching to a different field increases by approximately 0.8 percentage points, as shown in Table S1.8. This shift is primarily driven by workers in labor-intensive crop fields, who show a 1.2 percentage-point increase in the probability of working in another field, while the coefficient for less labor-intensive crops is about half that size. The results show that workers move to mitigate the effect of smoke. The median worker moves 18.7 miles to avoid smoke, with workers in the first quartile moving 8.1 miles and those in the third quartile moving 42.5 miles.

When analyzing the effects based on smoke densities, as illustrated in Figure 1.9 and Table S1.9, we find a 0.65 percentage-point increase in the likelihood of working in different fields on days when light smoke covers a worker's usual field. On days with moderate smoke, there is a 1.12 percentage-point increase.

Finally, the coefficient for heavy-smoke days exhibits the largest magnitude, indicating a 1.35 percentage-point increase in the likelihood of working in other fields. However, this effect is not statistically significant, possibly because of the small number of field-days exposed to heavy smoke.

As a robustness check, we replicate our main empirical exercise using a measure of smoke exposure based on $PM_{2.5}$ rather than atmospheric smoke plumes. As described above, we use a validated measure of $PM_{2.5}$ from wildfire smoke (Childs et al., 2022). These data have been used to study the causal effects of smoke-induced $PM_{2.5}$ on various outcomes such as emergency-department visits (Heft-Neal et al., 2023b), mobility, sentiments (Burke et al., 2022), and education (Wen and Burke, 2022).

Our empirical approach here is directly analogous to equations 1.2 and 1.4, and equations 1.3 and 1.5, save that we use smoke-induced $PM_{2.5}$ as our treatment variables instead of smoke plumes. In this setup, $PM_{2.5}$ is assigned a value of 1 if the $PM_{2.5}$ concentration from smoke exceeds 0, and 0 otherwise. The results align closely with previous results regarding smoke exposure. Table 3.2 presents the outcomes: when a field is affected by $PM_{2.5}$ from wildfire smoke, the number of workers in the field decreases by 18.08%, while working hours drop by 22.7% compared to regular days.

TABLE 1.7. $PM_{2.5}$ and Farmworker Outcomes: Extensive and Intensive Margin

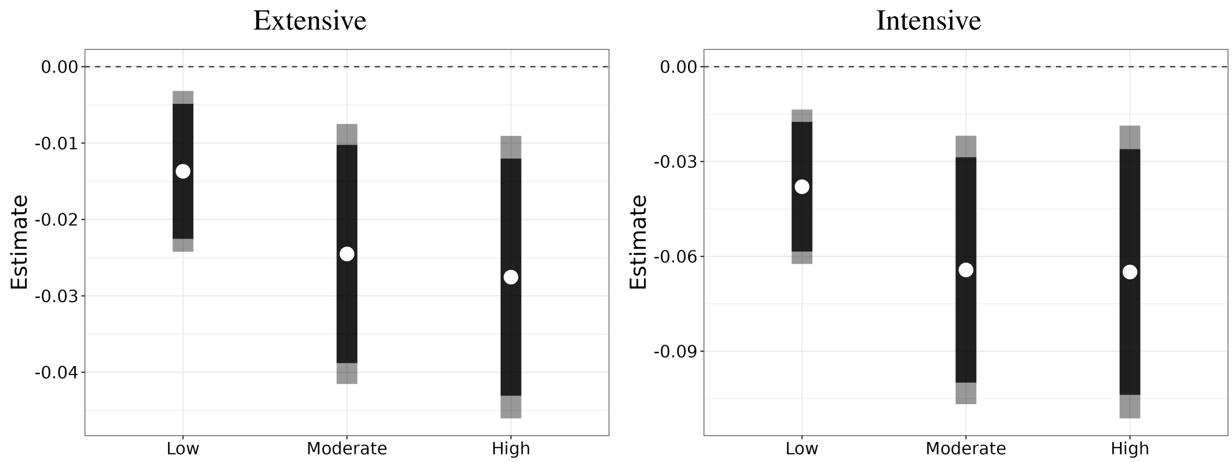
	(1)	(2)	(3)	(4)	(5)
A: Extensive					
$PM_{2.5}$	0.1258***	-0.0155**	-0.0181**	-0.0143***	-0.0134***
	(0.0111)	(0.0071)	(0.0078)	(0.0054)	(0.0051)
Dep. var. mean	0.1129	0.1129	0.1129	0.1129	0.1129
Control. mean	0.0791	0.0791	0.0791	0.0791	0.0791
Observations	3,941,550	3,941,550	3,941,550	3,941,550	3,941,550
R^2	0.03331	0.06692	0.60134	0.60297	0.07608
B: Intensive					
$PM_{2.5}$	0.2801***	-0.0443***	-0.0476***	-0.0394***	-0.0351***
	(0.0250)	(0.0162)	(0.0179)	(0.0127)	(0.0117)
Dep. var. mean	0.2467	0.2467	0.2467	0.2467	0.2467
Control. mean	0.1736	0.1736	0.1736	0.1736	0.1736
Observations	3,941,550	3,941,550	3,941,550	3,941,550	3,941,550
R^2	0.01395	0.02889	0.52838	0.52910	0.03379
Weather and fire Controls	✓	✓	✓	✓	✓
Week fixed effects		✓			
Field-by-week fixed effects			✓	✓	
Weekend fixed effects				✓	✓
County-by-week fixed effects					✓

To parallel our main analysis, we categorize smoke-induced $PM_{2.5}$ levels into three groups: low, moderate, and high. Low levels are defined as $PM_{2.5}$ concentrations between 0 μg/m^3 and 20 μg/m^3, moderate levels range from 20 μg/m^3 to 40 μg/m^3, and high levels exceed 40 μg/m^3. We find that at higher $PM_{2.5}$ levels, estimated responses are larger, as shown in Figure 1.10 and Table S1.11 at both the extensive and intensive margins. On days when $PM_{2.5}$ falls in the high bin, the number of workers in the field falls by 34.89%, and working hours fall by 37.38 % relative to days without smoke-induced $PM_{2.5}$.

1.5. Discussion and Conclusion

Understanding the effects of wildfires on farmers' and farmworkers' labor decisions is timely and important for workers and farmers alike given the anticipated increase in the frequency and intensity of wildfires caused by a changing climate. The results are relevant for policy makers seeking to protect workers'

FIGURE 1.10. $PM_{2.5}$ and Farmworker Labor: Extensive and Intensive Margin



Notes: The bottom labels refer to three levels of $PM_{2.5}$ density. Dark lines show their 90% and 95% confidence intervals. All regressions include field × week and weekend fixed effects, daily-maximum-temperature bins, and controls for precipitation, precipitation squared, and distance to fire. Standard errors are two-way clustered by field and date.

health, safety, and well-being and to ensure the sustainability of one of the most productive agricultural regions in the world.

We provided the first quasi-experimental evidence of the effect of wildfire events on farmworker labor outcomes. Agricultural labor responds to wildfires by significantly reducing days and hours worked. Farmworkers working in labor-intensive crop fields, who likely face greater health risks, experience a larger reduction than farmworkers working in less labor-intensive crop fields. We found evidence that workers substitute across time and space, mitigating the overall impact of wildfires on production and worker wages. Estimates that ignore this dynamic, adaptive behavior overstate the net effects of wildfire smoke on workers and employers. While our novel movement data allow new insights along some dimensions, they have a number of limitations along others: our sample period consists of a single growing season, and occupation is inferred from plausible criteria rather than being observed directly.

Our results suggest a level of adaptation that is likely less than desirable from a public health perspective. Even at low densities, exposure to smoke poses important health hazards. Prior work suggests that being exposed to $PM_{2.5}$, even in small amounts, for either short or long periods, can raise the risk of mortality (Deryugina et al., 2019; Di et al., 2017a,b; Miller et al., 2021). The risk is especially high for those exposed to smoke from wildfires (Aguilera et al., 2021). Beatty and Lee (2023) find that light- and moderate-density smoke lead to increases in farmworker injuries relative to the absence of smoke. However, we find only about a 15%–30% reduction in the number of workers in fields or the number of working hours on days with light and moderate densities of smoke.

One potential reason for the small response is that the PM threshold that triggers mitigation measures is relatively high. For example, when $PM_{2.5}$ levels exceed 55.5 μg/m^3 in California and Washington or 35.5 μg/m^3 in Oregon, employers are required to implement measures to protect workers from wildfire smoke. Given that the threshold is well above the median $PM_{2.5}$ level we observe in fields covered with light- or moderate-density smoke—24.54 μg/m^3—current thresholds may be too high to encourage adaptation on days with light- or moderate-density smoke.

Another possible explanation for the relatively small response is that farmworkers might not be aware of their right to use paid sick leave or may fear retaliation if they do not turn up for work or if they work fewer hours. In a recent survey of farmworkers (Ridgway et al., 2022), 23% of participants indicated that they had no knowledge of their right to three days of paid sick leave. And among the farmworkers who were aware of their right to sick leave and asked to reduce working hours because of poor working conditions, 12% were retaliated against. However, if we consider the wider economic impacts of smoke, rather than just its effects on public health, we might find compensatory benefits on smoky days, such as higher wages driven by increased labor demand. A complete accounting of the welfare effects of wildfire smoke on farmworker labor would need to account for these factors.

While our unique data allowed us to identify novel margins of substitution, we were limited in what we could say about mechanisms. We observed an equilibrium outcome and could not distinguish between farmworkers reducing labor supply and farmers reducing labor demand in response to wildfire smoke. Increasing risks from wildfires may exacerbate the chronic shortage of agricultural labor (Rutledge and Taylor, 2019). Understanding the mechanisms of adaptation and the long-run effects of wildfire on labor outcomes are important topics for both future research and policy development. Furthermore, while using cell-phone location data offers valuable insights, it suffers a potential limitation: the possibility of occasional coverage loss due to wildfire damage to cellular communication networks (Guyot et al., 2021). This could lead to instances in which worker observations are missing in smoke-affected areas, which would result in an underestimate of the effects of wildfire smoke on work attendance and hours.

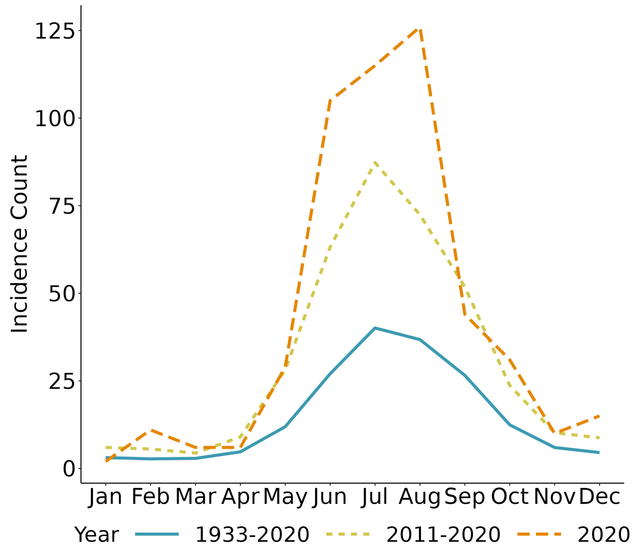
Finally, because of the difficulty in tracking and surveying farmworkers, the impact of climate change on agricultural labor in particular and workers more broadly is understudied (Behrer and Park, 2017; Dillender, 2021; Kjellstrom and Crowe, 2011; Neidell et al., 2021) despite the importance and urgency of the question (Alston et al., 2021). This paper demonstrates the potential, and a few of the limitations, of big-data approaches to answer first-order questions in labor, environmental, and agricultural economics that cannot be addressed with conventional data sources.

1.6. Appendix

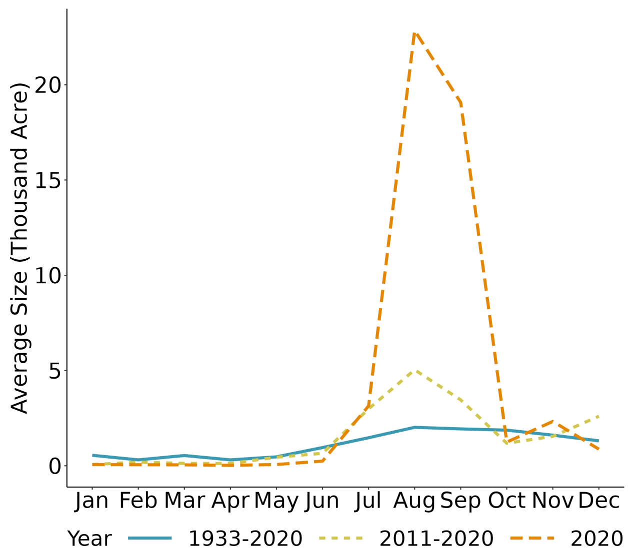
1.6.1. Data.

FIGURE S1.1. The Number of Incidence and Average Size Trends of Wildfire

(a) The Number of Wildfire Incidences by Month



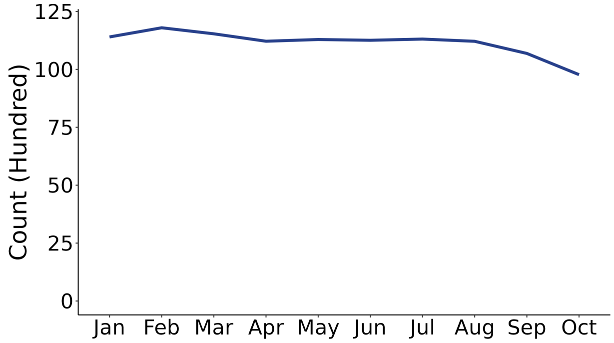
(b) The Average Size of Wildfire Incidences by Month



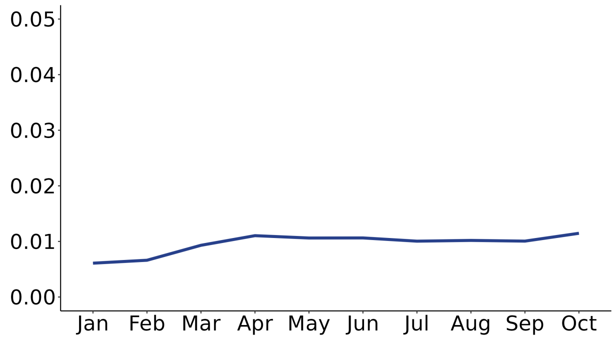
Notes: The graph in panel (a) illustrates the average yearly frequency of wildfire occurrences per month during the periods 1933-2020, 2011-2020, and 2020 in California. Panel (b) shows the annual average size (Acre) of fire per incidence by month during the periods 1933-2020, 2011-2020, and 2020 in California. Different colors stand for the different sample periods. Data is retrieved from the Fire and Resource Assessment Program (FRAP) (FRAP, 2022).

FIGURE S1.2. The Number of Individuals Observed by Month

(a) Farmworkers by Month

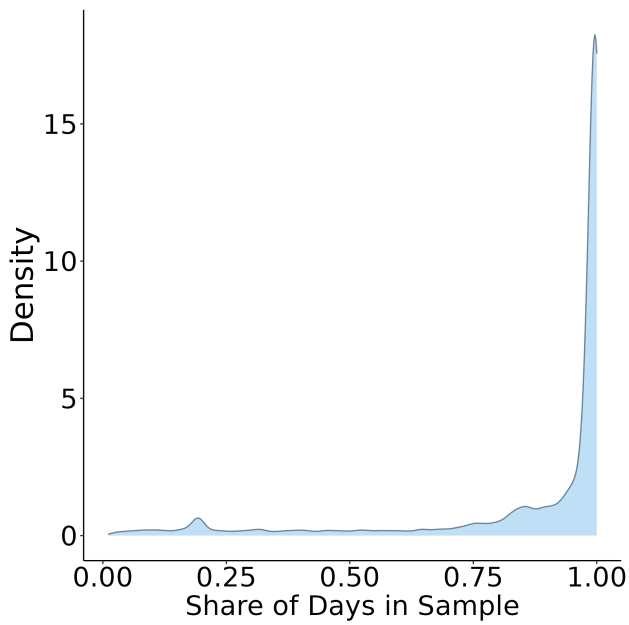


(b) Proportion of Farmworkers to all Individuals



Notes: Panel (a) presents the number of farmworkers observed by month and panel (b) shows the proportion of farmworkers to all individuals found in the mobile location tracking data by month.

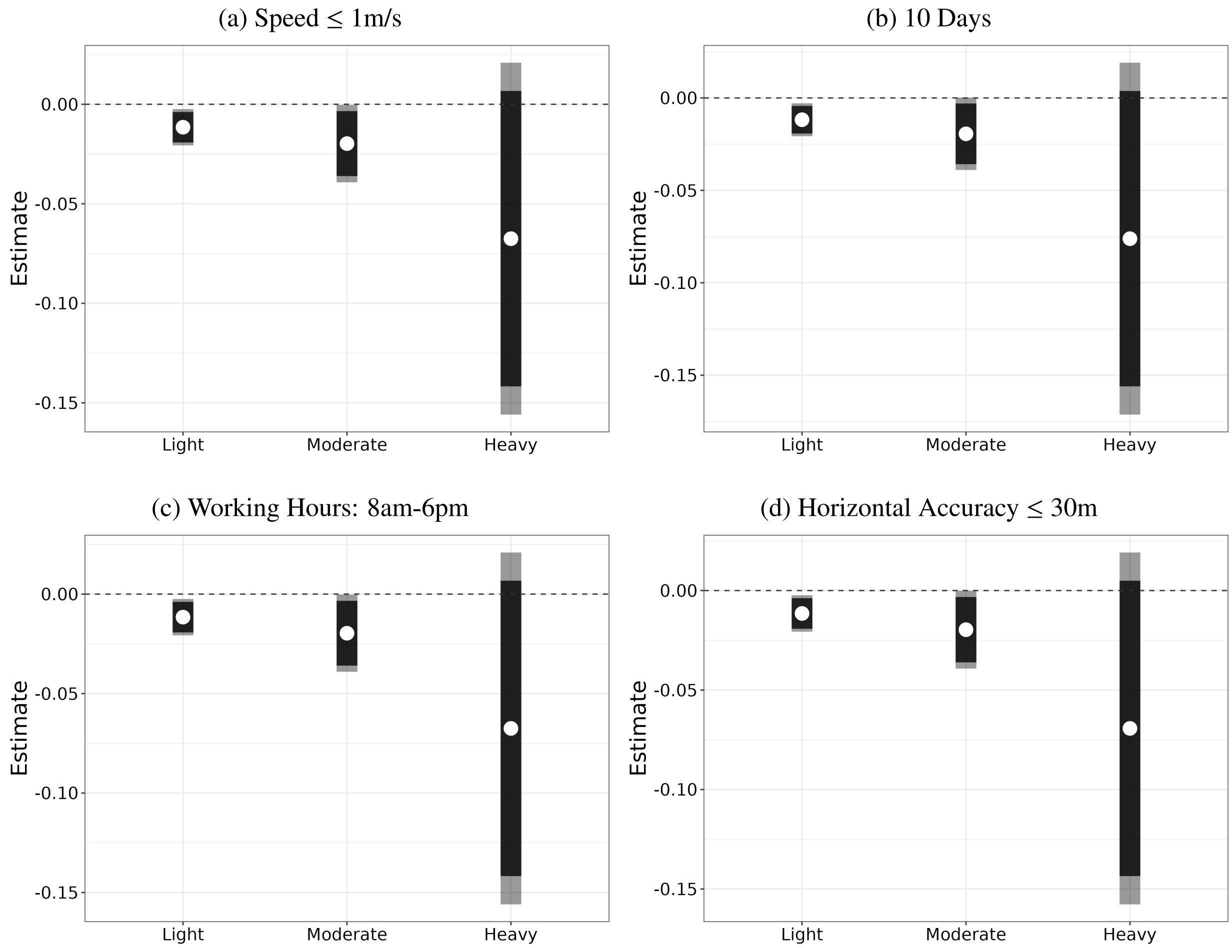
FIGURE S1.3. The Share of Days Using Apps



Notes: The x-axis represents the proportion of days that individuals are observed in the sample relative to the entire sample period.

1.6.2. Robustness Check.

FIGURE S1.4. Criteria of Farmworkers



Notes: Figure S1.4 shows the estimation results of extensive margin analysis corresponding to the main results in figure 1.5 when all other criteria are equal, but we change one criterion at a time. Panel (a) shows the results when we only retain individuals who move less than or equal to 1 m/s. Panel (b) is the result when we only keep observations that appear 10 or more days in a month in any field instead of 5 days. The result in panel (c) defines working hours from 8 am to 6 pm compared to the main results that use the 6 am-8 pm definition and panel (d) drops observations with horizontal accuracy greater than 30 m compared to the criteria of 62 m in the main findings.

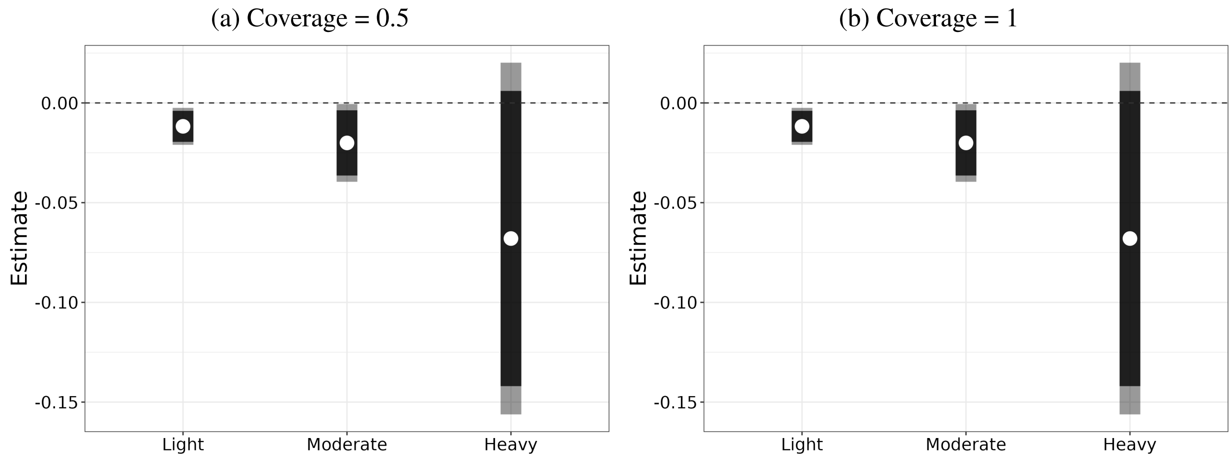
1.6.2.1. *Farmworkers Criteria.*

1.6.2.2. *Definition of Modal Field.* In the main analysis, we define the modal field relative to the previous two weeks. To check the sensitivity of results to the choice of this time interval, we present the results of substitution over space analysis of smoke when we instead define a modal field relative to the previous week or month in Table S1.1. Even if the coefficients do not perfectly align with the main analysis, they are consistent with the finding that wildfire smoke results in an increase in the probability of farmworkers switching to another field.

TABLE S1.1. Substitution over Space

(A) Week	(1)	(2)	(3)	(4)	(5)
Smoke	0.0057	0.0117***	0.0150***	0.0125***	0.0121**
	(0.0044)	(0.0043)	(0.0046)	(0.0046)	(0.0049)
Dep. var. mean	0.6974	0.6974	0.6974	0.6974	0.6974
Control. mean	0.6911	0.6911	0.6911	0.6911	0.6911
Observations	660,867	660,867	660,867	660,867	660,867
R^2	0.41081	0.41137	0.51580	0.51599	0.41454
(B) Month					
Smoke	0.0038	0.0080***	0.0078**	0.0065**	0.0073**
	(0.0028)	(0.0028)	(0.0033)	(0.0033)	(0.0033)
Dep. var. mean	0.6936	0.6936	0.6936	0.6936	0.6936
Control. mean	0.6911	0.6911	0.6911	0.6911	0.6911
Observations	693,576	693,576	693,576	693,576	693,576
R^2	0.42279	0.42331	0.52257	0.52263	0.42602
Weather and fire Controls	✓		✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓
Week fixed effects		✓			
Field-by-week fixed effects			✓	✓	
Weekend fixed effects				✓	✓
County-by-week fixed effects					✓

FIGURE S1.5. Different Geographical Coverage



Notes: Figure S1.5 presents results corresponding to regression equation 1.3. Panel (a) and (b) depict results when we define a field is treated by smoke only where more than 50% and 100% of the field is covered with smoke, respectively.

1.6.2.3. *Spatial Aggregation of Smoke.* In our main analysis, we consider a field to be covered with smoke if any part of it is affected. We experiment with different criteria to define fields that are covered with smoke to check the robustness of our analysis. As shown in figure S1.5, there are almost no changes in the results as only 0.072% of our sample is partially covered with smoke.

1.6.2.4. *Temporal Aggregation of Smoke.* When the satellite image sequence used to draw the smoke polygon overlaps throughout a day, we take an average of the overlapping layers of smoke densities by the day for our main analysis. To evaluate the robustness of the result depending on our smoke aggregation choice, we construct smoke data in alternative ways. We pick the maximum density of the overlapping smoke layers and conduct the same analysis that corresponds to the regression equation 1.3. Table S1.2 present results. While the coefficients may not perfectly match the results of the main analysis, they are consistent with the finding that wildfire smoke decreases the number of farmworkers in a field and working hours.

TABLE S1.2. Extensive and Intensive Margin

(A) Extensive	(1)	(2)	(3)	(4)	(5)
Light	0.1006***	-0.0103*	-0.0148**	-0.0116**	-0.0104**
	(0.0112)	(0.0062)	(0.0065)	(0.0046)	(0.0041)
Moderate	0.1293***	-0.0210**	-0.0262**	-0.0188**	-0.0180**
	(0.0121)	(0.0099)	(0.0123)	(0.0091)	(0.0085)
Heavy	0.1350***	-0.0263**	-0.0348**	-0.0219*	-0.0197*
	(0.0132)	(0.0123)	(0.0169)	(0.0123)	(0.0118)
Dep. var. mean	0.1129	0.1129	0.1129	0.1129	0.1129
Control. mean	0.0788	0.0788	0.0788	0.0788	0.0788
Observations	3,941,550	3,941,550	3,941,550	3,941,550	3,941,550
R^2	0.03336	0.06695	0.60138	0.60298	0.07608
(B) Intensive					
Light	0.2238***	-0.0294**	-0.0408***	-0.0338***	-0.0290***
	(0.0252)	(0.0132)	(0.0144)	(0.0105)	(0.0093)
Moderate	0.2801***	-0.0702***	-0.0717**	-0.0555**	-0.0526**
	(0.0269)	(0.0244)	(0.0304)	(0.0233)	(0.0222)
Heavy	0.3023***	-0.0798***	-0.0891**	-0.0608**	-0.0507*
	(0.0300)	(0.0305)	(0.0406)	(0.0305)	(0.0290)
Dep. var. mean	0.2467	0.2467	0.2467	0.2467	0.2467
Control. mean	0.1730	0.1730	0.1730	0.1730	0.1730
Observations	3,941,550	3,941,550	3,941,550	3,941,550	3,941,550
R^2	0.01394	0.02893	0.52840	0.52911	0.03380
Weather and fire Controls	✓	✓	✓	✓	✓
Week fixed effects		✓			
Field-by-week fixed effects			✓	✓	
Weekend fixed effects				✓	✓
County-by-week fixed effects					✓

1.6.3. Tables.

1.6.3.1. *Extensive Margin.*

TABLE S1.3. Smoke and Farmworker Labor: Extensive Margin

	(1)	(2)	(3)	(4)	(5)
Light	0.1006***	-0.0101	-0.0146**	-0.0115**	-0.0104**
	(0.0112)	(0.0062)	(0.0065)	(0.0047)	(0.0042)
Moderate	0.1333***	-0.0232**	-0.0294**	-0.0199**	-0.0184*
	(0.0124)	(0.0106)	(0.0138)	(0.0099)	(0.0094)
Heavy	0.0315	-0.1205**	-0.0822	-0.0661	-0.1094***
	(0.0495)	(0.0472)	(0.0559)	(0.0453)	(0.0233)
Dep. var. mean	0.1129	0.1129	0.1129	0.1129	0.1129
Control. mean	0.0788	0.0788	0.0788	0.0788	0.0788
Observations	3,941,550	3,941,550	3,941,550	3,941,550	3,941,550
R^2	0.03336	0.06696	0.60138	0.60298	0.07609
Weather and fire Controls	✓	✓	✓	✓	✓
Week fixed effects		✓			
Field-by-week fixed effects			✓	✓	
Weekend fixed effects				✓	✓
County-by-week fixed effects					✓

Notes: Dep. var. mean represents the mean of the dependent variable and Control. mean indicates the mean of the control group. Here, control group mean implies the number of workers in field when there is no smoke. Standard errors are two-way clustered by field and date.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

TABLE S1.4. Smoke and Farmworker Labor: Intensive Margin

	(1)	(2)	(3)	(4)	(5)
Light	0.2237***	-0.0290**	-0.0404***	-0.0336***	-0.0290***
	(0.0252)	(0.0132)	(0.0145)	(0.0105)	(0.0093)
Moderate	0.2956***	-0.0741***	-0.0781**	-0.0573**	-0.0512**
	(0.0278)	(0.0261)	(0.0334)	(0.0251)	(0.0238)
Heavy	0.0434	-0.2977**	-0.1763*	-0.1410*	-0.2707***
	(0.1169)	(0.1202)	(0.1023)	(0.0810)	(0.0676)
Dep. var. mean	0.2467	0.2467	0.2467	0.2467	0.2467
Control. mean	0.1730	0.1730	0.1730	0.1730	0.1730
Observations	3,941,550	3,941,550	3,941,550	3,941,550	3,941,550
R^2	0.01393	0.02893	0.52840	0.52911	0.03380
Weather and fire Controls	✓	✓	✓	✓	✓
Week fixed effects		✓			
Field-by-week fixed effects			✓	✓	
Weekend fixed effects				✓	✓
County-by-week fixed effects					✓

Notes: Dep. var. mean represents the mean of the dependent variable and Control. mean indicates the mean of the control group. Here, control group mean implies the average working hours in field when there is no smoke. Standard errors are two-way clustered by field and date.

1.6.3.2. *Intensive Margin.*

TABLE S1.5. Intensive Margin: More Labor Intensive vs Less Labor Intensive

(A) Labor Intensive	(1)	(2)	(3)	(4)	(5)
Smoke	0.2528***	-0.0340	-0.0635***	-0.0491***	-0.0467***
	(0.0264)	(0.0216)	(0.0230)	(0.0167)	(0.0153)
Dep. var. mean	0.2086	0.2086	0.2086	0.2086	0.2086
Control. mean	0.1437	0.1437	0.1437	0.1437	0.1437
Observations	1,047,660	1,047,660	1,047,660	1,047,660	1,047,660
R^2	0.01379	0.03106	0.47892	0.48022	0.03962
(B) Less Labor Intensive					
Smoke	0.2802***	-0.0480***	-0.0464***	-0.0370***	-0.0315***
	(0.0250)	(0.0141)	(0.0158)	(0.0118)	(0.0105)
Dep. var. mean	0.2605	0.2605	0.2605	0.2605	0.2605
Control. mean	0.1837	0.1837	0.1837	0.1837	0.1837
Observations	2,893,890	2,893,890	2,893,890	2,893,890	2,893,890
R^2	0.01376	0.02851	0.54129	0.54187	0.03419
Weather and fire Controls	✓	✓	✓	✓	✓
Week fixed effects		✓			
Field-by-week fixed effects			✓	✓	
Weekend fixed effects				✓	✓
County-by-week fixed effects					✓

1.6.3.3. *Intensive Margin: Tasks.*

1.6.3.4. *Substitution Over Time: Extensive Margin.*

TABLE S1.6. Substitution over Time - Extensive Margin

	(1)	(2)	(3)	(4)	(5)
Pre 3	0.0451	0.0147	0.0111	0.0087	0.0079
	(0.0279)	(0.0128)	(0.0122)	(0.0084)	(0.0074)
Pre 2	0.0639**	0.0215*	0.0134	0.0156*	0.0157**
	(0.0286)	(0.0114)	(0.0111)	(0.0080)	(0.0066)
Pre 1	0.0713***	0.0186	0.0120	0.0183**	0.0176**
	(0.0242)	(0.0143)	(0.0145)	(0.0092)	(0.0084)
Event Date	0.0893***	-0.0176	-0.0315**	-0.0203*	-0.0179**
	(0.0293)	(0.0138)	(0.0156)	(0.0106)	(0.0084)
Post 1	0.0450*	-0.0143	-0.0222	-0.0263**	-0.0243***
	(0.0246)	(0.0127)	(0.0139)	(0.0103)	(0.0092)
Post 2	0.0391	-0.0050	-0.0146	-0.0217**	-0.0185*
	(0.0252)	(0.0137)	(0.0137)	(0.0109)	(0.0100)
Post 3	0.0221	-0.0105	-0.0157	-0.0244**	-0.0220**
	(0.0246)	(0.0170)	(0.0172)	(0.0117)	(0.0110)
Dep. var. mean	0.2297	0.2297	0.2297	0.2297	0.2297
Control. mean	0.1779	0.1779	0.1779	0.1779	0.1779
Observations	1,091,238	1,091,238	1,091,238	1,091,238	1,091,238
R^2	0.00543	0.01682	0.62979	0.63296	0.02939
Weather and Fire Controls	✓	✓	✓	✓	✓
Week fixed effects		✓			
Field-week fixed effects			✓	✓	
Weekend fixed effects				✓	✓
County-week fixed effects					✓

Notes: Event date is defined as a day when a field is covered with any level of smoke. Pre j denotes j days before the event, and Post j denotes j days after the event.

1.6.3.5. *Substitution Over Time: Intensive Margin.*

TABLE S1.7. Substitution over Time - Intensive Margin

	(1)	(2)	(3)	(4)	(5)
Pre 3	0.1314**	0.0549*	0.0465	0.0410*	0.0393**
	(0.0646)	(0.0326)	(0.0310)	(0.0211)	(0.0193)
Pre 2	0.1600***	0.0602**	0.0429	0.0480**	0.0474**
	(0.0594)	(0.0274)	(0.0272)	(0.0217)	(0.0184)
Pre 1	0.1660***	0.0430	0.0260	0.0406*	0.0407**
	(0.0514)	(0.0316)	(0.0334)	(0.0221)	(0.0198)
Event Date	0.2097***	-0.0496	-0.0809**	-0.0549**	-0.0451**
	(0.0623)	(0.0304)	(0.0344)	(0.0228)	(0.0187)
Post 1	0.1096**	-0.0301	-0.0474	-0.0570**	-0.0515**
	(0.0547)	(0.0291)	(0.0312)	(0.0231)	(0.0208)
Post 2	0.0762	-0.0287	-0.0485	-0.0649***	-0.0580***
	(0.0524)	(0.0298)	(0.0301)	(0.0243)	(0.0222)
Post 3	0.0566	-0.0265	-0.0392	-0.0592**	-0.0538**
	(0.0572)	(0.0370)	(0.0382)	(0.0257)	(0.0235)
Dep. var. mean	0.5000	0.5000	0.5000	0.5000	0.5000
Control. mean	0.3731	0.3731	0.3731	0.3731	0.3731
Observations	1,091,238	1,091,238	1,091,238	1,091,238	1,091,238
R^2	0.00241	0.00793	0.53718	0.53889	0.01467
Weather and Fire Controls	✓	✓	✓	✓	✓
Week fixed effects		✓			
Field-week fixed effects			✓	✓	
Weekend fixed effects				✓	✓
County-week fixed effects					✓

Notes: Event date is defined as a day when a field is covered with any level of smoke. Pre j denotes j days before the event, and Post j denotes j days after the event.

1.6.3.6. *Substitution Over Space.*

TABLE S1.8. Smoke and Farmworker Labor: Substitution over Space

(A) All	(1)	(2)	(3)	(4)	(5)
Smoke	0.0058*	0.0097***	0.0096**	0.0080**	0.0092**
	(0.0032)	(0.0032)	(0.0037)	(0.0036)	(0.0037)
Dep. var. mean	0.6948	0.6948	0.6948	0.6948	0.6948
Control. mean	0.6915	0.6915	0.6915	0.6915	0.6915
Observations	657,813	657,813	657,813	657,813	657,813
R^2	0.41132	0.41179	0.51397	0.51405	0.41482
(B) Labor Intensive					
Smoke	0.0064	0.0147***	0.0141***	0.0120**	0.0122**
	(0.0043)	(0.0046)	(0.0054)	(0.0053)	(0.0051)
Dep. var. mean	0.7646	0.7646	0.7646	0.7646	0.7646
Control. mean	0.7670	0.7670	0.7670	0.7670	0.7670
Observations	165,010	165,010	165,010	165,010	165,010
R^2	0.36830	0.36945	0.47518	0.47537	0.37801
(C) Less Labor Intensive					
Smoke	0.0060**	0.0081***	0.0081**	0.0067*	0.0083**
	(0.0029)	(0.0030)	(0.0035)	(0.0034)	(0.0034)
Dep. var. mean	0.6714	0.6714	0.6714	0.6714	0.6714
Control. mean	0.6654	0.6654	0.6654	0.6654	0.6654
Observations	492,803	492,803	492,803	492,803	492,803
R^2	0.42276	0.42314	0.51987	0.51993	0.42659
Weather and fire Controls	✓		✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓
Week fixed effects		✓			
Field-by-week fixed effects			✓	✓	
Weekend fixed effects				✓	✓
County-by-week fixed effects					✓

TABLE S1.9. Substitution over Space by Smoke Density

	(1)	(2)	(3)	(4)	(5)
Light	0.0058**	0.0083***	0.0074**	0.0065*	0.0081**
	(0.0029)	(0.0030)	(0.0034)	(0.0033)	(0.0035)
Moderate	0.0058	0.0121***	0.0140***	0.0112**	0.0115**
	(0.0037)	(0.0039)	(0.0049)	(0.0047)	(0.0046)
Heavy	-0.0212	-0.0165	0.0156	0.0135	-0.0181
	(0.0245)	(0.0277)	(0.0314)	(0.0304)	(0.0242)
Dep. var. mean	0.6948	0.6948	0.6948	0.6948	0.6948
Control. mean	0.6915	0.6915	0.6915	0.6915	0.6915
Observations	657,813	657,813	657,813	657,813	657,813
R^2	0.41132	0.41179	0.51397	0.51405	0.41482
Weather and fire Controls	✓		✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓
Week fixed effects		✓			
Field-by-week fixed effects			✓	✓	
Weekend fixed effects				✓	✓
County-by-week fixed effects					✓

TABLE S1.10. Smoke and Farmworker Labor by the Number of Days Observed

(A) Extensive	(1) 5 Days	(2) 20 Days	(3) 30 Days
Smoke	-0.0086**	-0.0182**	-0.0213**
	(0.0034)	(0.0072)	(0.0089)
Dep. var. mean	0.0633	0.1773	0.2430
Observations	9,000,300	1,915,200	1,101,525
R^2	0.55404	0.65307	0.69456
(B) Intensive			
Smoke	-0.0232***	-0.0606***	-0.0793***
	(0.0071)	(0.0186)	(0.0253)
Dep. var. mean	0.1270	0.4240	0.6300
Observations	9,000,301	1,915,200	1,101,525
R^2	0.50918	0.54741	0.56248
Weather and fire Controls	✓	✓	✓
Field-by-week fixed effects	✓	✓	✓
Weekend fixed effects	✓	✓	✓

Notes: Panel (A) presents the estimation results for the extensive margin, while panel (B) displays the results of the intensive margin analyses. We retain fields based on the number of days observed. For example, if any workers in a field are observed for 30 days or more in the sample, we retain that field and drop fields that are observed for fewer than 30 days.

1.6.3.7. *Robustness Checks.*

1.6.3.8. $PM_{2.5}$.

TABLE S1.11. $PM_{2.5}$ and Farmworker Outcomes: Continuous and Three Levels of $PM_{2.5}$

	Extensive	Intensive
Low	-0.0137**	-0.0380***
	(0.0054)	(0.0125)
Moderate	-0.0245***	-0.0643***
	(0.0087)	(0.0217)
Heavy	-0.0276***	-0.0649***
	(0.0094)	(0.0236)
R^2	0.60299	0.52911
Continuous $PM_{2.5}$	-0.0003*	-0.0005
	(0.0001)	(0.0004)
R^2	0.60295	0.52908
Dep. var. mean	0.1129	0.2467
Control. mean	0.0791	0.1736
Observations	3,941,550	3,941,550
Weather and fire Controls	✓	✓
Field-by-week fixed effects	✓	✓
Weekend fixed effects	✓	✓

CHAPTER 2

Wildfires and Agricultural-Worker Injury

2.1. Introduction

This paper explores the short-run consequences of wildfire-smoke exposure on agricultural workers' occupational safety and health. Wildfires are a salient and growing threat to public health and agricultural workers are at particular risk. Wildfire season overlaps with peak harvest season in the western United States, regularly exposing agricultural workers to elevated levels of particulate matter and air toxics. Because they work outdoors and engage in vigorous physical activity, agricultural workers face greater risks than workers in other industries. Exposure poses an immediate threat to agricultural workers' health through increased risk of cardiovascular and respiratory disorders (Black et al., 2017; DeFlorio-Barker et al., 2019; Heft-Neal et al., 2023c; Liu et al., 2017; Reid et al., 2016; Wettstein et al., 2018) and potentially an increased risk of traumatic injuries (Akesaka and Shigeoka, 2023; Burton and Roach, 2023; Dillender, 2021; Park et al., 2021). This threat is large and growing, the United States experienced a doubling in the area burned by wildfires (Abatzoglou and Williams, 2016) in recent decades, and under most climate change scenarios the frequency and intensity of fires will grow (Abatzoglou and Williams, 2016; NOAA, 2022b).

Existing work on the health effects of air pollution has largely focused on the general population, with greater attention given to vulnerable groups such as infants, children, and the elderly (Beatty and Shimshack, 2011, 2014; Chay and Greenstone, 2003; Currie and Neidell, 2005; Deryugina et al., 2019; Ebenstein et al., 2017; Knittel et al., 2016; Schlenker and Walker, 2016). A challenge in studying agricultural workers' health is that approximately half of the farmworker population in the United States is undocumented (Martin, 2015). Undocumented persons are less likely to have health insurance and are less likely to participate in safety net programs, which makes studying their health and well-being challenging (Gold et al., 2021; Hill, 2016). In studying agricultural workers, we add to a growing environmental justice literature examining the effect of air pollution on disadvantaged groups (Arceo et al., 2016; Heft-Neal et al., 2020; Jbaily et al., 2022).

We also contribute to an emerging literature linking air pollution to an increased risk of traumatic injuries (Akesaka and Shigeoka, 2023; Burton and Roach, 2023; Dillender, 2021; Park et al., 2021). Smoke can impair cognitive performance (Lai et al., 2022; Wen and Burke, 2022) and increase risky behavior (Homberg, 2012; Murphy et al., 2013; Pattij and Vanderschuren, 2008). Air-pollution exposure can increase levels of stress-related hormones that may increase impatience and alter work behavior (Li et al., 2017; Riis-Vestergaard et al., 2018). Further, discomfort caused by smoke can lead to blurred vision and itchy eyes, which can increase the chances of a traumatic injury. Research on the health effects of air pollution has largely focused on respiratory and cardiovascular illnesses (Schlenker and Walker, 2016) or mortality (Chay and Greenstone, 2003; Currie and Neidell, 2005; Heft-Neal et al., 2020; Jayachandran, 2009; Miller et al., 2021).

To answer our research questions, we use compensation-claims data from California's Workers' Compensation Information System (WCIS) for 2007 to 2021. Agricultural employers in California are required to provide workers'-compensation coverage for both permanent and seasonal employees. As a result, WCIS data cover documented agricultural workers and, critically, also cover undocumented agricultural workers. This data set allows us to investigate the short-run impact of environmental factors on agricultural workers' occupational health and safety.

We merge WCIS data with wildfire-smoke data and $PM_{2.5}$ levels. Identifying the health effects of environmental conditions can be challenging. Average wildfire-smoke exposure may be associated with a range of factors that also affect injuries. However, daily exposure at the local level is largely random, influenced by factors such as the locations and timing of fire outbreaks and daily wind patterns. For $PM_{2.5}$, the challenge is isolating variation in air pollution not driven by factors that directly affect injuries. To address this issue, we adopt a well-validated measure of exogenous zip-code and day variation in wildfire-induced smoke and $PM_{2.5}$ (Burke et al., 2022; Childs et al., 2022; Heft-Neal et al., 2023c; Wen and Burke, 2022).

We find that wildfire-smoke-induced $PM_{2.5}$ has a significant impact on workplace injuries; a 10 μg/m^3 increase in daily $PM_{2.5}$ exposure from wildfire smoke increases traumatic injuries by 2.3 percent. Our estimate of the impact of wildfire smoke on agricultural workers' injuries is comparable to Deryugina et al.'s (2019) estimate for the elderly population, a demographic vulnerable to the effects of air-pollution exposure (Deryugina et al., 2019). We explore nonlinearities in the dose-response function and find large effect sizes at higher exposures of the kind that have become more frequent in recent years. We explore heterogeneity by age and find younger workers are more likely to suffer an injury caused by wildfire smoke relative to older workers. A back-of-the-envelope calculation finds that wildfire smoke was responsible for approximately 282 additional agricultural workers' injuries per year in California. As the likelihood of wildfire events is projected to increase by the end of the century, with estimates ranging from 1.3 to 1.6 times the current rate (Sullivan et al., 2022), our results suggest the effects of wildfire smoke on agricultural workers will grow, absent policy changes.

From a policy perspective, our findings suggest that daily variations in $PM_{2.5}$ have economically significant effects on agricultural workers' injuries, even at levels below the current policy-relevant threshold of 50 μg/m^3, which triggers outdoor-worker protection policies. We also find evidence that air pollution has a significant impact on traumatic injuries and disproportionately affect younger workers. Policies aimed at safeguarding workers from wildfire smoke have traditionally been limited to mitigating the well-established impacts on respiratory and cardiovascular outcomes – our work suggests that a broader focus is likely warranted.

The paper is organized as follows. Section 2 provides background on the smoke-injury relationship. Section 3 explains our data sources and how we constructed our data set. Section 4 describes our research design. Section 5 presents our main results. Section 6 discusses the implications of our paper and concludes.

2.2. Background

Exposure to wildfire smoke is dangerous. Wildfire smoke results from the combustion of organic materials such as wood, generating a complex blend of gases and fine particles. Of these, fine particulate matter ($PM_{2.5}$) is a major public health concern and its effects on cardiovascular and respiratory disorders are well documented (Black et al., 2017; DeFlorio-Barker et al., 2019; Heft-Neal et al., 2023c; Liu et al., 2017; Reid et al., 2016; Wettstein et al., 2018). Primary risks come from changes in pulmonary and cardiovascular functioning (Seaton et al., 1995). This results in asthma attacks and cardiovascular events, such as heart attacks, which in turn lead to hospitalizations and mortality (Dockery and Pope, 1994). Research suggests that $PM_{2.5}$ from wildfires is more dangerous than $PM_{2.5}$ from other sources; some studies estimate that its health effects are an order of magnitude larger (Aguilera et al., 2021).

A growing literature links adverse environmental conditions, such as air pollution and extreme temperatures, to traumatic injuries (Akesaka and Shigeoka, 2023; Burton and Roach, 2023; Dillender, 2021; Park et al., 2021). Using workers'-compensation records across the universe of jobs in California, Park et al. (2021) find that extreme temperatures increase workplace injuries by 4.8% relative to mild temperatures, where traumatic injuries account for most the increase. Using Texas workers'-compensation data, Dillender (2021) find that occupational injury rates are increasing in ambient temperatures. In related work, Akesaka and Shigeoka (2023) find that increases in daily pollen count are associated with increased occupational injuries.

Several mechanisms have been put forward to explain how air pollution and smoke can lead to traumatic injuries. First, $PM_{2.5}$ exposure diminishes cognitive performance. Air pollution can impair respiratory function and circulation, leading to reduced oxygen supply to the brain, resulting in decreased concentration, delayed reflexes, and confusion (Kampa and Castanas, 2008). Experimental evidence finds that short-term exposure to elevated PM concentration, such as that found when burning candles or commuting outdoors, significantly impairs cognitive function (Shehab and Pope, 2019). Ambient $PM_{2.5}$ exposure reduces cognitive performance as measured by test scores (Ebenstein et al., 2016; Wen and Burke, 2022). There is evidence that exposure to $PM_{2.5}$ can cause momentary lapses in concentration (Sunyer et al., 2017). Given the dangerous nature of farm work—for example, operating heavy machinery, cutting lettuce, or picking fruits on ladders—diminished cognitive function and lapses in concentration may lead to traumatic injuries.

Second, $PM_{2.5}$ may increase traumatic injuries by creating stress-related behavior change. Studies have linked acute air-pollution exposure with elevated levels of hormones such as cortisol, cortisone, and epinephrine (Li et al., 2017). Elevated stress-hormone levels can lead to distraction, attention narrowing, and increased muscle tension, which can lead to injuries (Andersen and Williams, 1988; Nippert and Smith, 2008; van Winden et al., 2021). Air pollution, particularly $PM_{2.5}$, can also increase the production of stress-related hormones such as serotonin (Murphy et al., 2013), potentially leading to more impulsive behavior and increased risk-taking tendencies (Homberg, 2012; Pattij and Vanderschuren, 2008). For example, individuals may be more likely to forgo safety measures, a behavior linked with increased injury risks (González-Recio et al., 2022; Westaby and Lee, 2003).

Finally, wildfire smoke can induce discomfort such as blurred vision and itchy eyes (Holm et al., 2021; Jaiswal et al., 2022). The impact of wildfire smoke on ocular symptoms, including irritation, grittiness, burning sensation, excessive watering, and dryness, has been documented in both the general population and among firefighters (Howard et al., 2020; Jaiswal et al., 2022; Kunzli et al., 2006). Impaired vision, particularly in high-risk work environments such as agriculture (NIFA, 2022), can increase the risk of traumatic injuries.

2.3. Data and Summary Statistics

To quantify the impact of wildfire smoke on agricultural-worker injuries, we use claims data from WCIS. We match the injury data with wildfire-smoke data from the National Oceanic and Atmospheric Administration's (NOAA's) Hazard Mapping System (HMS) and data on wildfire-driven-$PM_{2.5}$ concentrations from Childs et al. (2022). Finally, we use weather data from PRISM (2021). This section details our data and sample construction procedure.

2.3.1. California's Workers' Compensation Information System. We use confidential injury-claims data from WCIS. What distinguishes WCIS data from other sources is its ability to identify agricultural workers. Unlike other administrative health data sets, incidents in the WCIS are tied to occupation and employer, which allows us to identify individuals employed in agriculture. Other sources of administrative health data, such as emergency room or inpatient visits, typically lack information regarding occupation.

Relative to other data on worker injuries, WCIS data offer a comprehensive account of workplace injuries in California. Critical for our purposes is that all agricultural workers in California are covered by workers' compensation, unlike many states that do not require employers to cover seasonal agricultural workers. Coverage of undocumented workers is key to answering our research question, as undocumented farmworkers make up over half of California's crop workers (Martin, 2015). California law requires all employers, regardless of size, to provide workers'-compensation insurance (DWC, 2020). According to the National Agricultural Workers Survey conducted in 2019–20, most (86.7%) farmworkers in California, both documented and undocumented, report having workers'-compensation coverage (Gold et al., 2021). The difference in coverage between documented and undocumented workers is small, with 89.6% of documented workers and 84% of undocumented workers reporting being covered by workers' compensation. Finally, relative to workers'-compensation programs in other states, California's program has a lower reporting threshold. Data from other states may only include cases involving the death of a worker or injuries of three or more workers (Park et al., 2021).

An entry in the WCIS system is generated when a treating physician files a Doctor's First Report of Occupational Illness or Injury (DFR) electronically within five days of initial treatment. This report is transmitted to the Division of Workers' Compensation and compiled by WCIS. The claims data include the date of injury and the zip code of the worksite where the injury took place. For the main analysis, we collapse 209,858 individual records to the zip-code-day level. We restrict the sample to zip codes with at least one injury to an agricultural worker at least once in the sample period. With these zip codes, we construct a balanced panel at the zip-code-day level. Results are robust to alternative choices such as restricting the sample to a smaller set of zip codes with multiple injuries.

There is a chance the reported date of injury is measured with error because of delayed reporting to the workers'- compensation division after the incident. Delayed reporting can also occur when workers seek medical attention several days after an incident or when acute injuries are treated initially in the emergency room before claims are submitted. As a robustness check, we estimate a version of our main specification using a three-to-five-day rolling average of injuries as the main outcome variable of interest. This is parallel to our main analyses, as discussed in section 2.5.

Table 2.1 shows summary statistics of injuries. There are an average of 0.027 injuries per zip-code-day. A limitation of workers'-compensation data is they may undercount actual injuries. Underreporting can arise from worker concerns about employer reactions and from a perception that an injury may not be serious enough to warrant reporting (Haiduven et al., 1999; Kyung et al., 2023; Pompeii et al., 2016; Rosenman et al., 2000). This may be particularly relevant for undocumented workers who may choose not to seek hospital care out of fear of potential retaliation from their employers. In addition, claims may be rejected if program administrators conclude there is insufficient evidence linking the injuries to work-related activities (CDIR, 2022). Fear of rejection may discourage workers from reporting chronic illnesses, such as respiratory and circulatory illnesses that are more challenging to attribute to specific work-related incidents, compared to acute outcomes such as traumatic injuries (Biddle, 2001; InvictusLaw, 2022).

As a result of the institutional context, respiratory and cardiovascular claims are relatively rare in our sample – 1,430 cases are reported between 2007 and 2021. This is roughly 0.8% of the total sample. For perspective, emergency room (ER) visits related to respiratory diseases in California during the same time period account for 11% of total ER visits (Heft-Neal et al., 2023c). Traumatic injuries, including strains or tears, contusions, and lacerations, are the most frequently reported injuries and account for 78.57% of total injuries in our sample.

TABLE 2.1. Summary Statistics: Injuries

Statistic	Mean	Median	Std Dev	Min	Max	N
All	0.027	0	0.201	0	93	8,657,654
Traumatic	0.021	0	0.167	0	24	8,657,654
Respiratory and Cardiovascular	0.0002	0	0.016	0	21	8,657,654
Respiratory	0.0001	0	0.013	0	21	8,657,654
Cardiovascular	0.0001	0	0.010	0	2	8,657,654
Mental Disorder	0.0001	0	0.009	0	3	8,657,654
Hernia	0.0002	0	0.014	0	2	8,657,654

Notes: This table presents summary statistics of farmworker injuries.

2.3.2. Smoke. We use wildfire-smoke data from NOAA's HMS to identify smoke-affected zip codes. These data provide smoke densities in California using near-real-time satellite observations (NOAA, 2022a). Analysts at NOAA process satellite images into georeferenced polygon data, which are then joined to individual zip codes. These data have been used to study the effects of wildfire smoke on employment (Borgschulte et al., 2022), health (Heft-Neal et al., 2023c), suicide (Molitor et al., 2023), and averting behavior (Burke et al., 2022).

To combine NOAA smoke data and WCIS compensation claims, we aggregate data to the zip code level for the period 2007 to 2021. Our primary measure of smoke exposure is a binary treatment indicator equal to one if any part of a zip code is covered by a smoke plume during working hours on a given day and zero otherwise. Results are robust to defining treatment as a zip code being entirely covered, as detailed in table S2.9. We focus on working hours, between 6 a.m. and 8 p.m., to better capture exposure during times when agricultural workers are likely to be at work. We extend our primary analysis using NOAA's classification of smoke plumes into three densities: light, medium, and heavy, corresponding to smoke concentrations spanning 0 to 10, 10 to 21, and 21 to 32 μg/m^3, respectively. If a zip code is covered with multiple smoke-density categories, we assign it the density covering the largest portion of the area.

2.3.3. $PM_{2.5}$. We also separately consider the effects of wildfire related $PM_{2.5}$. We do this for several reasons. Smoke data are derived from satellite aerial images, thus smoke plumes and ground-level $PM_{2.5}$

may differ despite being highly correlated, as shown in figure 2.1. More broadly, many workplace health and safety regulations are written in terms of $PM_{2.5}$ levels and so results for $PM_{2.5}$ exposure speak directly to policy. In addition, the health impacts of $PM_{2.5}$ are well-studied, which allows for a direct comparison of our estimates to earlier work.

One challenge to estimating the effect of $PM_{2.5}$ from smoke on agricultural-worker injuries is that variation in ambient $PM_{2.5}$ may come from sources other than wildfires, such as nearby roads and factories. Further, the number of monitoring stations is limited, both over time and across space. To deal with this issue, we use Childs et al.'s (2022) data. This data isolates $PM_{2.5}$ from wildfires and has been used to explore the impacts of wildfire $PM_{2.5}$ emissions on health outcomes (Heft-Neal et al., 2023c), educational performance (Wen and Burke, 2022), and averting behavior (Burke et al., 2022).

Variable construction proceeds in several steps. First, anomalies in $PM_{2.5}$ are calculated by subtracting median $PM_{2.5}$ values observed on smoke-free days from the baseline $PM_{2.5}$ concentrations at each monitoring station:[1]

$$\widetilde{\mathrm{PM}}_{idmy} = \mathrm{PM}_{idmy} - \overline{\mathrm{PM}}^{\mathrm{NS}}_{imy}$$

Here, PM_{idmy} denotes the $PM_{2.5}$ concentration at station i on day d in month m and year y and $\overline{\mathrm{PM}}^{\mathrm{NS}}_{imy}$ denotes median $PM_{2.5}$ at station i and month m in the three-year window when there was no smoke. This median value is computed as

$$\overline{\mathrm{PM}}^{NS}_{imy} = \mathrm{median}\left(\left\{\mathrm{PM}_{idmy} \mid i = I, m = M, Y-1 \leq y \leq Y+1, \mathrm{smoke}_{idmy} = 0\right\}\right),$$

where smoke_{idmy} is a binary variable indicating whether a day is a smoke or nonsmoke day. Subsequently, to compute a measure for smoke-induced abnormal $PM_{2.5}$, denoted as $\mathrm{SmokePM}_{idmy}$, $\widetilde{\mathrm{PM}}_{idmy}$ is multiplied by the binary variable smoke_{idmy} as follows:

$$\mathrm{SmokePM}_{\ idmy} = \max\left(\widetilde{\mathrm{PM}}_{idmy} \times \ \mathrm{smoke}_{\ idmy}, 0\right)$$

Because of the limited and changing number of monitoring stations, Childs et al. (2022) use a statistical model to capture the local and temporal variation of wildfire-induced smoke. Using machine learning techniques and incorporating data such as weather, fire (from HMS), and elevation data, they generate a

[1]The data on daily average $PM_{2.5}$ concentration is sourced from Environmental Protection Agency monitoring stations. Smoke days are defined using smoke-plume data from HMS and simulated air-packet trajectories from smoke-producing fire points detected by HMS using the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model.

SmokePM grid with a spatial resolution of 10×10 km^2. We aggregate the SmokePM grids to the zip code level by averaging the values within each zip code and day. This aggregation process provides a zip code specific measure of SmokePM concentration.

Prior work documents a nonlinear relationship between SmokePM exposure and various outcomes (Beatty and Lee, 2024b; Chang et al., 2016; Heft-Neal et al., 2023c; Miller et al., 2021). We categorize SmokePM into three bins to investigate its potentially nonlinear relationship with agricultural-worker injuries. We classify SmokePM in zip code z on day d according to: Low as $0\ \mu g/m^3 < \text{SmokePM}_{z,d} \leq 10\ \mu g/m^3$, Medium as $10\ \mu g/m^3 < \text{SmokePM}_{z,d} \leq 20\ \mu g/m^3$, and High as $\text{SmokePM}_{z,d} \geq 20\ \mu g/m^3$.

2.3.4. Weather. Weather data come from PRISM (PRISM, 2021). We control for daily maximum temperature and total precipitation. PRISM divides the United States into 4×4 km^2 grids. In robustness checks, we add controls for wind patterns. We use wind-speed and wind-direction data from the Gridded Surface Meteorological (gridMET) data set (Abatzoglou, 2013), which records the daily wind direction and wind speed in a 4×4 km^2 grid. Using the grids, we construct weather data at the zip code level by averaging the grid values covering a zip code.

We combine our wildfire-smoke and weather data at the zip code level at a daily timescale. Following this, we join this data set with our injury data, which records the number of workers injured by zip code and date. We conduct a parallel process by merging $PM_{2.5}$ from smoke with the workers'-injury data and weather data, matching zip code and date.

2.3.5. Summary Statistics.

TABLE 2.2. Summary Statistics: Smoke and $PM_{2.5}$

Statistic	Mean	Median	Std Dev	Min	Max	N
Panel A: Smoke						
% Days Smoke	0.079	0	0.269	0	1	8,657,654
% Days Light	0.051	0	0.219	0	1	8,657,654
% Days Moderate	0.015	0	0.123	0	1	8,657,654
% Days Heavy	0.013	0	0.112	0	1	8,657,654
Days/Year Smoke	28.345	23	24.767	0	118	24,075
Days/Year Light	18.238	18	13.628	0	58	24,075
Days/Year Moderate	5.530	3	6.711	0	38	24,075
Days/Year Heavy	4.577	0	8.886	0	62	24,075
Panel B: $PM_{2.5}$						
% Days 0 <SmokePM	0.079	0	0.270	0	1	8,657,654
% Days Low	0.063	0	0.242	0	1	8,657,654
% Days Medium	0.008	0	0.088	0	1	8,657,654
% Days High	0.008	0	0.092	0	1	8,657,654
Days/Year 0 <SmokePM	28.373	21	25.826	0	138	24,075
Days/Year Low	22.540	20	17.538	0	107	24,075
Days/Year Medium	2.779	0	4.918	0	45	24,075
Days/Year High	3.054	0	7.829	0	74	24,075

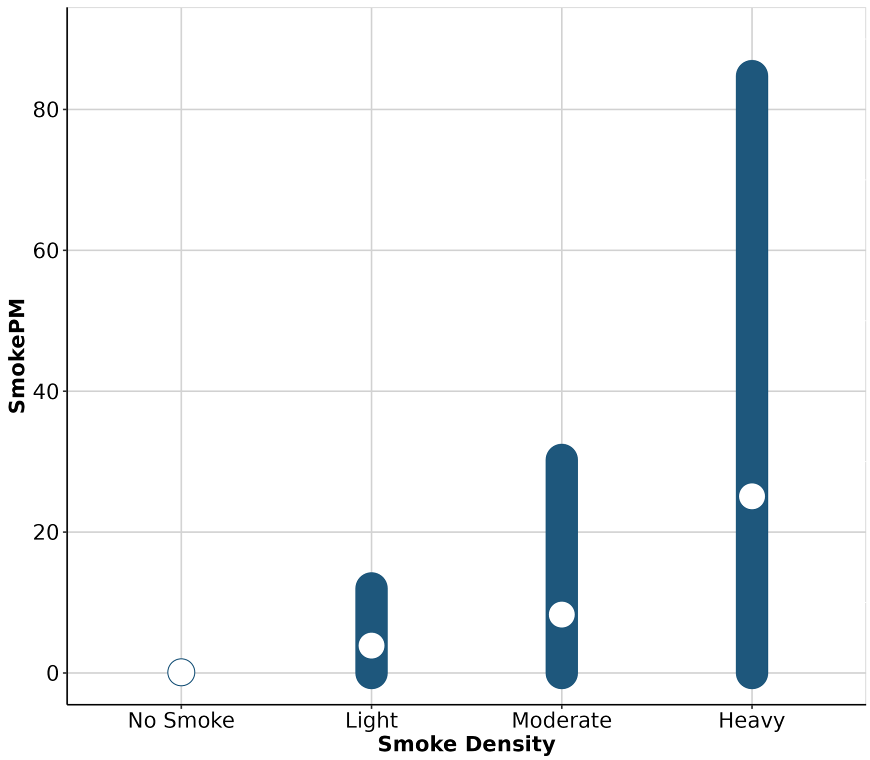
Notes: This table presents summary statistics of key treatment variables. It collapses smoke and $PM_{2.5}$ information by zip code and day. Panel A provides information on samples for smoke analysis. Panel B provides information on the sample for $PM_{2.5}$ analysis. In panel B, Low is defined as $0\ \mu g/m^3 <$ SmokePM $\leq 10\ \mu g/m^3$, Medium as $10\ \mu g/m^3 <$ SmokePM $\leq 20\ \mu g/m^3$, and High as $20\ \mu g/m^3 \leq$ SmokePM.

Figure S2.1 plots spatial variation in injuries, smoke, and $PM_{2.5}$ from smoke in California. Smoke density and SmokePM are highly correlated, with SmokePM levels being higher when smoke is denser as shown in panels (a) and (b). Note, SmokePM has more variation because smoke densities are only recorded in three levels, while the SmokePM variable is constructed using continuous $PM_{2.5}$ values from monitoring stations.

Table 2.2 presents summary statistics of zip code–level exposure to smoke and $PM_{2.5}$. On average, a zip code experienced smoke events or $PM_{2.5}$ events from wildfire about one month per year in our sample period. Each year in a given zip code, episodes of light smoke occur about 18 days, moderate smoke 6 days, and heavy smoke about 5 days. The numbers are similar in the case of $PM_{2.5}$ for different densities.

Figure S2.2 shows changes in injuries, smoke, and $PM_{2.5}$ events over time. The numbers of both agricultural-worker injuries and wildfire-smoke events tend to increase over the sample period. Agriculture-related injuries appear to be seasonal with injuries occurring more around harvesting season. Wildfire season matches peak employment season for California's agricultural workforce, which leads to increased injuries from around May to October.

FIGURE 2.1. Correlation between Smoke and $PM_{2.5}$



Notes: The figure shows the correlation between smoke density and smoke particulate matter (SmokePM). The dots in the middle of the lines represent the average SmokePM for each smoke density. The lines on the graph represent the 95th and 5th percentiles of SmokePM for each level of smoke density.

Figure 2.1 shows the correlation between three levels of smoke-density data and the SmokePM variable. The average values of SmokePM increase as the smoke density increases. For days with heavy-density smoke, the average SmokePM is 25.08 $\mu g/m^3$.

2.4. Research Design

To causally identify treatment effects, we rely on plausibly exogenous daily fluctuations in both wildfire smoke, and $PM_{2.5}$ from wildfire smoke, concentrations within zip codes. Individual wildfires can be viewed as random events and wildfire smoke is randomly dispersed by wind across large distances. This creates an exogenous source of variation in smoke levels unaffected by factors influencing the underlying economic conditions.

For all specifications, we use a Poisson quasi-maximum likelihood model (PQML) that captures the non-negative and discrete nature of our outcome data. This approach has been used to investigate the influence of environmental conditions on count outcomes, including health outcomes (Akesaka and Shigeoka, 2023; Park et al., 2021; Schlenker and Walker, 2016) and crime (Bondy et al., 2020; Burkhardt et al., 2019; Johnson et al., 2020; Ranson, 2014), either as a main specification or as a robustness check. The PQML estimator provides consistent estimates of regression coefficients even in cases where the equidispersion condition, which requires the equality of the mean and variance of the dependent variable, is violated (Silva and Tenreyro, 2011). Formally, we estimate the following model:

$$\text{Injuries}_{\text{z,d}} = exp(\beta\,\text{Smoke}_{\text{z,d}} + \mathbf{W}_{z,d}\Pi + \alpha_{ym} + \delta_{zy})\epsilon_{z,d} \tag{2.1}$$

$$\text{Injuries}_{\text{z,d}} = exp(\beta_1\,\text{Light}_{\text{z,d}} + \beta_2\,\text{Medium}_{\text{z,d}} + \beta_3\,\text{Heavy}_{\text{z,d}} + \mathbf{W}_{z,d}\Pi + \alpha_{ym} + \delta_{zy})\epsilon_{z,d} \tag{2.2}$$

Here, $\text{Injuries}_{\text{z,d}}$ denotes the count of injuries in zip code z on day d. $\text{Smoke}_{z,d}$ denotes whether zip code z experiences a smoke event on day d. $\text{Light}_{\text{z,d}}$ (0–10 μg/m^3), $\text{Medium}_{\text{z,d}}$ (10–21 μg/m^3), and $\text{Heavy}_{\text{z,d}}$ (21–32 μg/m^3) denote the density of smoke. $\mathbf{W}_{z,d}$ denotes weather. Prior work has found that temperatures and wildfire smoke can jointly affect health outcomes (Chen et al., 2024) and so $\mathbf{W}_{z,d}$ includes 15 maximum daily temperature intervals, starting below 40°F and rising in 5°F increments until exceeding 105°F. Additionally, $\mathbf{W}_{z,d}$ contains four categories of total daily precipitation: days with no precipitation and days with precipitation greater than zero to less than half an inch, from half an inch to less than one inch, and at least one inch. α_{ym} denotes year-by-month fixed effects that remove shocks specific to a year-month such as seasonality in the demand agricultural labor (for example, harvest seasons) and also seasonality in wildfires by year. δ_{zy} denotes zip-code-by-year fixed effects that account for unobserved variation coming from zip code–specific annual shocks, such as a change in the composition of the type of crops in a given zip code. $\epsilon_{z,d}$ denotes an idiosyncratic error specific to a zip code and date. Standard errors are clustered at the zip-code-year level. The main results using equations 2.2 and 2.4 are robust to alternative clustering choices such as zip code and year and month, county and date, and county and year as presented in table S2.8.

We also consider the effects of $PM_{2.5}$ from wildfire smoke on worker injuries. As above, we estimate models of the following form:

$$\text{Injuries}_{\text{z,d}} = exp(\beta\, \text{SmokePM}_{\text{z,d}} + \mathbf{W}_{z,d}\Pi + \alpha_{ym} + \delta_{zy})\epsilon_{z,d} \tag{2.3}$$

$$\text{Injuries}_{\text{z,d}} = exp(\beta_1\, \text{Low}_{\text{z,d}} + \beta_2\, \text{Medium}_{\text{z,d}} + \beta_3\, \text{High}_{\text{z,d}} + \mathbf{W}_{z,d}\Pi + \alpha_{ym} + \delta_{zy})\epsilon_{z,d} \tag{2.4}$$

Equation 2.3 imposes a linear dose-response on the equilibrium relationship between smoke and injuries while equation 2.4 allows the equilibrium dose-response function to vary across exposure levels. $\text{SmokePM}_{\text{i,z}}$ represents the continuous $PM_{2.5}$ concentration derived from wildfire smoke. Low is defined as 0 μg/m^3 < $\text{SmokePM}_{\text{z,d}}$ ≤ 10 μg/m^3, Medium as 10 μg/m^3 < $\text{SmokePM}_{\text{z,d}}$ ≤ 20 μg/m^3, and High as 20 μg/m^3 ≤ $\text{SmokePM}_{\text{z,d}}$.

2.5. Results

TABLE 2.3. Relationship between Traumatic Injuries, Smoke, and $PM_{2.5}$

	(1)	(2)	(3)	(4)	(5)
(A) Smoke					
Smoke	0.2048**	0.0732***	0.1624***	0.0599**	0.0769***
	(0.0717)	(0.0209)	(0.0403)	(0.0237)	(0.0216)
Dep. var. mean	0.0213	0.0213	0.0213	0.0213	0.0213
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
(B) SmokePM					
SmokePM	0.0083***	0.0024***	0.0060***	0.0024**	0.0023***
	(0.0010)	(0.0006)	(0.0010)	(0.0008)	(0.0006)
Dep. var. mean	0.0213	0.0213	0.0213	0.0213	0.0213
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
Weather controls	✓		✓	✓	✓
Year x month fixed effects		✓			✓
Zip x year fixed effects		✓			✓
Year fixed effects			✓		
Zip x month fixed effects			✓		
Year x month x zip fixed effects				✓	

Notes: Table 2.3 reports the results of equations 2.1 and 2.3 for both the smoke and SmokePM variables. 'Dep.var.mean' shows the average number of traumatic injuries by zip code and day. Standard errors are based on estimates clustered by zip code and year. * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

We begin by estimating the impact of smoke and $PM_{2.5}$ on traumatic injuries, which make up the majority of injuries reported in WCIS. The results from the regressions are shown in table 2.3, covering five sets of fixed effects. Each coefficient in panel (A) represents the semielasticity of the total number of injuries for a smoke-impacted day relative to a smoke free day.

Column (5) presents the results of our preferred specification, which includes year-by-month and zip-code-by-year fixed effects. The year-by-month fixed effects absorb monthly seasonality common to all zip codes by year. The zip-code-by-year fixed effects remove unobserved variation coming from zip code–specific annual shocks, such as economic conditions. We find that on days with smoke, traumatic injuries increase by 7.99% compared to days without smoke.

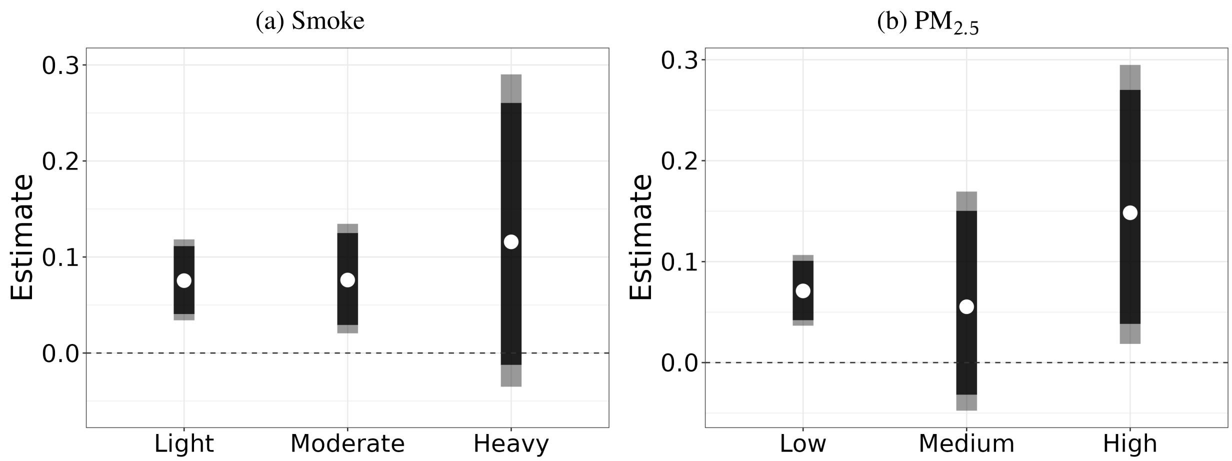
Column (1) presents the regression results with weather controls but without two-way fixed effects. In the absence of any fixed effects, the coefficient's magnitude is larger than our preferred specification, suggesting that accounting for those fixed effects is crucial for estimating the relationship between smoke and injuries. Column (2) includes year-by-month and zip-code-by-year fixed effects, as in our preferred specification, but without weather controls. The estimate remains little changed compared to the results with weather controls, indicating that the correlation between weather conditions and smoke has minimal effects on our estimate. Additionally, we control for wind direction and wind speed, and the results are presented in table S2.10. Estimated coefficients are directly comparable in terms of signs, significance, and magnitude relative to specifications without wind controls.

In column (3), we include year and zip-code-by-month fixed effects instead of year-by-month and zip-code-by-year fixed effects. The coefficient is almost twice as large as the estimate in our preferred specification, suggesting that there may still be some endogeneity stemming from seasonal variation by year in smoke and injury. However, including zip-code-by-year-by-month fixed effects, as in column (4), eliminates any variation common to a zip code in a given year and month. Not surprisingly, the magnitude of the coefficient in column (4) is smaller than that in column (5).

Turning to smoke-induced $PM_{2.5}$, in our preferred specification presented in column (5) in panel (B), we find that a 10 μg/m^3 increase in daily $PM_{2.5}$ exposure from wildfire smoke increases traumatic injuries by about 2.3%. Because this is the first paper to use workers'-compensation claims to assess the impacts of smoke-induced $PM_{2.5}$ on agricultural workers, we cannot assess whether estimated magnitudes are reasonable by comparing them with earlier studies. An imperfect comparison is the estimates from Deryugina et al.'s (2019) Medicare data covering beneficiaries aged 65 to 100 years in the United States. Deryugina et al. (2019) find that a 10 μg/m^3 increase in daily $PM_{2.5}$ exposure leads to a 2.22% rise in one-day all-cause hospitalizations. Our estimate for agricultural workers is directly comparable to estimates for the elderly reported by Deryugina et al. (2019). This seems plausible as both the elderly and agricultural workers have been found to be more vulnerable to smoke exposure compared to the general population.

Results are robust to a host of alternative choices, including estimating equivalent specifications using ordinary least squares (OLS), clustering standard errors at different levels, and estimates using a rolling-average of our outcome variable, all of which are reported in the appendix. Results for our main specifications estimated via OLS are presented in table S2.1. When we use OLS, effect sizes are slightly larger than our preferred approach. Specifically, a 10 μg/m^3 increase in daily $PM_{2.5}$ exposure from wildfire smoke increases injuries by 2.89% in OLS compared to 2.3% in the Poisson model. We also explore robustness to choices for clustering standard errors for both the smoke and Smoke related $PM_{2.5}$ outcome variables and report results in table S2.8; results are directly comparable across different levels. Last, we conduct parallel analyses following equation 2.3 but with three-, four-, and five-day rolling averages of injuries in the model (table S2.11). Our analysis shows that the estimates of rolling averages show a slight increase as we expand our rolling window to 5 days. This indicates that our main result provides a conservative estimate of the relationship between SmokePM and traumatic injuries.

FIGURE 2.2. The Nonlinear Relationship between Traumatic Injuries, Smoke, and $PM_{2.5}$



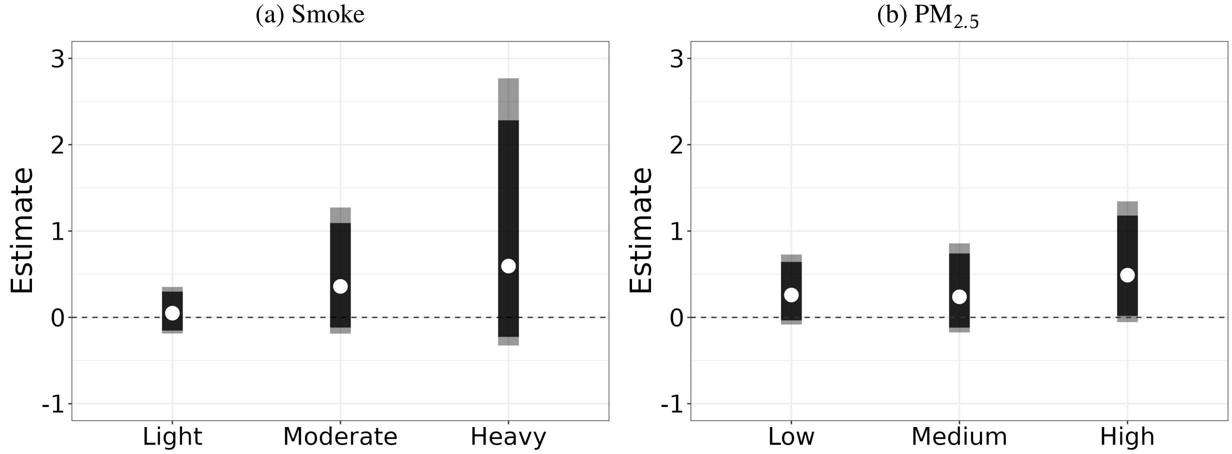
Notes: Panel (a) shows the relationship between smoke and traumatic injuries, and panel (b) shows the relationship between $PM_{2.5}$ from smoke and traumatic injuries. The plotted dots in the center represent the coefficients, indicating the incremental impacts of wildfire smoke on traumatic injuries. These effects are presented as percentage changes and are derived from Poisson regression estimations using equations 2.2 and 2.4. The labels at the bottom indicate three levels of smoke and $PM_{2.5}$ concentration. The solid lines indicate the 90% and 95% confidence intervals of the estimations.

Prior work finds the dose-response relationship between particulate-matter exposure and health outcomes is nonlinear: increments of exposure have larger effects at higher levels of exposure (Chang et al., 2016; Miller et al., 2021; Schlenker and Walker, 2016). To this end, we estimate the regression in equations 2.2 and 2.4 and show the results in figure 2.2, table S2.2, and table S2.3. We find that effect sizes tend to increase as smoke becomes denser and $PM_{2.5}$ levels increase. As shown in column (5) in table S2.2, the number of injuries by zip code and day increases by about 7.54% in zip codes with light smoke, 7.61% with moderate smoke, and 11.57% with heavy smoke compared to days without smoke, although the effect is imprecisely estimated for heavy smoke. The results are similar for the effects of wildfire-induced $PM_{2.5}$, showing a 6.8% increase in injuries on days with low levels of $PM_{2.5}$ and 14.29% on days with high levels. The category of days with heavy smoke has the smallest number of occurrences among the three smoke density categories. Similarly, the category of days with medium $PM_{2.5}$ concentration is the smallest among three $PM_{2.5}$ concentration categories.

Comparing our estimates to earlier work on temperature effects on workplace injuries, Park et al. (2021) finds that wholesale-trade workers in California experience a 15% increase in injuries on days with temperatures ranging from 95°F to 100°F compared to mild-weather days. This effect size is comparable to the impact of high levels of wildfire-induced $PM_{2.5}$ on traumatic injuries found in our study. Results are also in keeping with previous findings on the health effects associated with wildfire smoke and wildfire-induced $PM_{2.5}$. Studies such as Miller et al. (2021) and Heft-Neal et al. (2023c) find significant health effects of smoke even at light and moderate wildfire-smoke density. For instance, Miller et al. (2021) examine the relationship between $PM_{2.5}$ and mortality caused by wildfire smoke, showing positive and significant effects across light, medium, and thick smoke-plume densities.

Our results capture the equilibrium effects of smoke and smoke-related $PM_{2.5}$ on injuries, but are lower bounds on the dose-response estimates of exposure to smoke and smoke-related $PM_{2.5}$, as fewer agricultural workers may be working when a zip code is impacted by wildfire smoke (Beatty and Lee, 2024b). If agricultural workers who are less sensitive to smoke are more likely to go to work when there is high air pollution, then our estimates of injury count may be smaller than a situation in which all workers are present in a zip code. In this sense, we observe the effect of smoke exposure on agricultural workers which includes both a biological and a behavioral response.

FIGURE 2.3. The Relationship between Injuries, Smoke, and $PM_{2.5}$: Respiratory and Cardiovascular Injuries

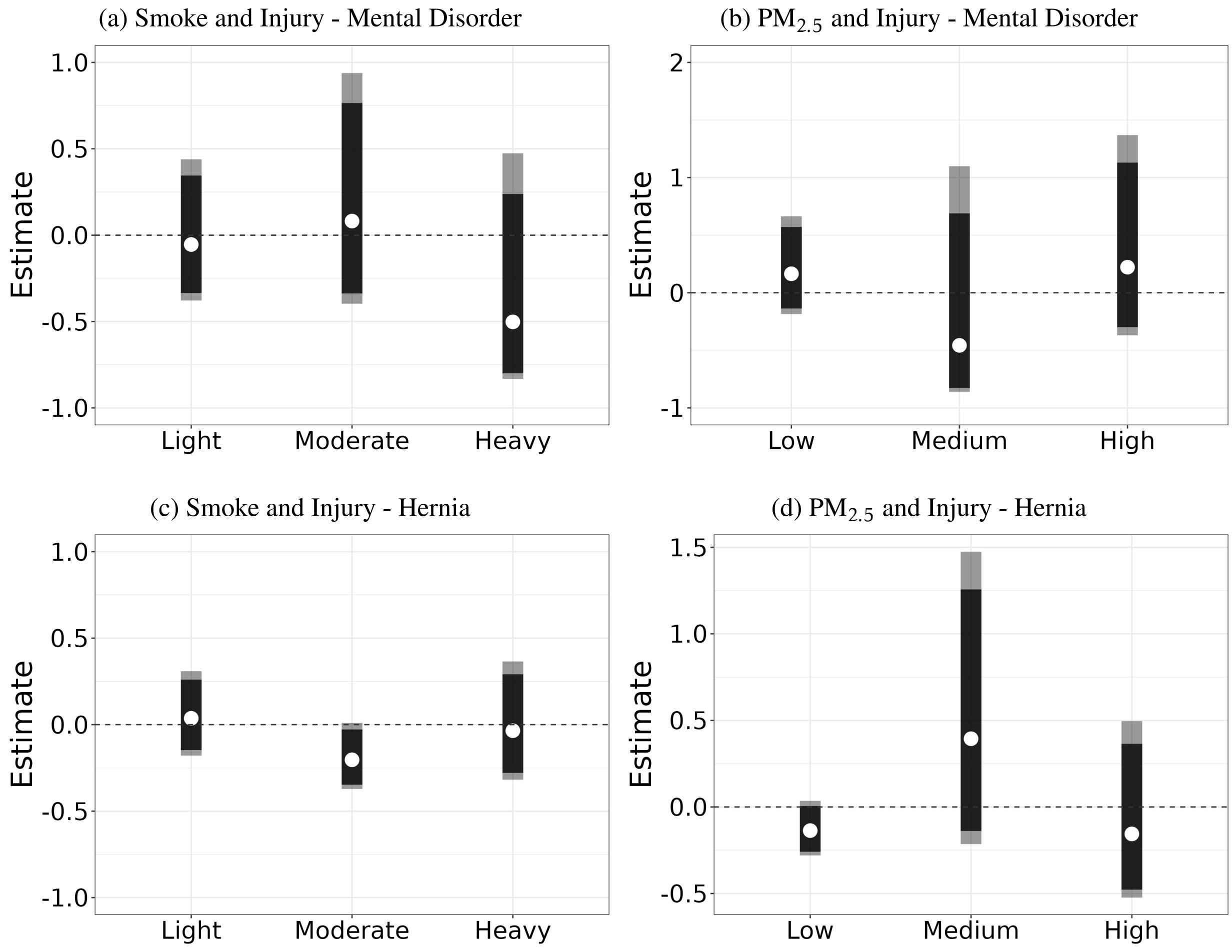


Notes: Panel (a) shows the relationship between smoke and respiratory and cardiovascular injuries, and panel (b) shows the relationship between $PM_{2.5}$ from smoke and the same injuries. The plotted dots in the center represent the coefficients, indicating the incremental impacts of wildfire smoke on injuries. These effects are presented as percentage changes and are derived from Poisson regression estimations using equations 2.2 and 2.4. The labels at the bottom indicate three levels of smoke and $PM_{2.5}$ concentration. The solid lines indicate the 90% and 95% confidence intervals of the estimations.

Next, we consider the impact of smoke and $PM_{2.5}$ on respiratory and cardiovascular injuries. Recall respiratory and cardiovascular injuries are relatively rare in workers' compensation claims data. Point estimates are reported in figure 2.3 and table S2.4. We find that a day with light smoke results in a 6.46% increase in respiratory and cardiovascular injuries, while moderate-smoke days see a 39.32% increase and heavy-smoke days show a 64.43% increase. Coefficients are imprecisely estimated, possibly due to the relatively small number of occurrences, but economically important. Point estimates for $PM_{2.5}$ are also imprecisely estimated and economically important. The lack of precision is due to the relatively small number of injuries that are classified as respiratory and cardiovascular diseases. They account for only 0.8% of reported cases. In contrast, the majority of cases (78.57%) are traumatic injuries. As explained in section 3, workers'-compensation data are not ideal for analyzing respiratory and cardiovascular injuries.

For completeness, we present regression results for all injury types in table S2.5. Estimates are similar to our traumatic-injury results, as traumatic injuries make up the lion's share of injuries in our data. Both smoke exposure and $PM_{2.5}$ from smoke exhibit statistically significant positive impacts on overall injuries.

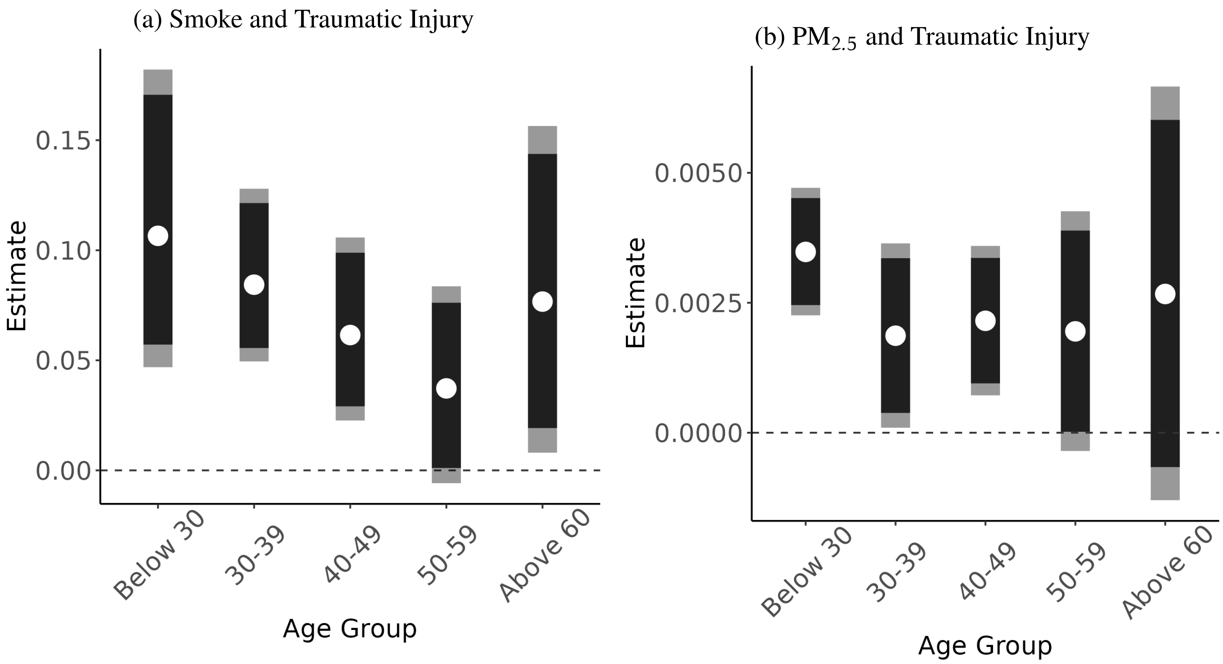
FIGURE 2.4. Robustness Tests



Notes: Figure 2.4 shows the regression results from equations 2.2 and 2.4 for injuries classified as mental disorders and hernia. Panels (a) and (b) present the effects of smoke and $SmokePM_{2.5}$ on mental disorders, and panels (c) and (d) show the respective effects on hernia injuries.

As a placebo test, we estimate the effects of wildfire smoke and smoke related particulate matter on injury types that are not typically associated with smoke. Employing the same specification as above 2.2 and 2.4, we estimate the effects of smoke on injuries related to mental disorders and hernia, which are unlikely to be caused by daily exposure to smoke. We find no significant effect of smoke and wildfire-smoke-induced $PM_{2.5}$ on either type of injury, as depicted in figure 2.4 and table S2.6. Furthermore, in contrast to the consistently positive and economically important coefficients observed for respiratory and cardiovascular injuries, the coefficients for the placebo categories are close to zero and some are negative.

FIGURE 2.5. The Relationship between Injuries, Smoke, and $PM_{2.5}$ by Age: Traumatic Injuries



Notes: The figure displays the regression results from equations 2.1 and 2.3 categorized by age groups. The age groups are delineated as follows: "Below 30" represents workers aged under 30, "30-39" between 30 and 39, "40-49" between 40 and 49, "50-59" between 50 and 59, and "Above 60" aged 60 and above. Panel (a) depicts the result for smoke analysis, and panel (b) shows the result for $PM_{2.5}$ analysis.

We now explore the effect of heterogeneity by worker age. Agriculture faces a persistent labor shortage (Charlton and Taylor, 2016; Hertz and Zahniser, 2013). This shortage can be attributed to various factors, including changes in population demographics, increased educational attainment among rural youths in Mexico, and better job opportunities outside of agriculture both in Mexico and the United States (Zahniser et al., 2018). One important factor is agricultural workers are getting older (Zahniser et al., 2018).

We find that smoke and $PM_{2.5}$ from smoke have the largest effects on younger workers. Figure 2.5 and table 3.5 report the results of equations 2.1 and 2.3 by age group. Specifically, for traumatic injuries as shown in panel (a) in figure 2.5, the impact of wildfire smoke is largest for workers younger than 30, with an 11.25% increase in injury count on smoky days. This effect is decreasing in age – results are not statistically significant for workers aged 50–59. However, estimated effect are larger for agricultural workers over 60. The effects of $PM_{2.5}$ in panel (b) exhibit a similar pattern. Results for respiratory and cardiovascular injuries are noisy but tell similar story and are presented in the appendix in figure S2.3.

While the gradient in effect size over age categories might seem surprising, prior work in the occupational health and safety literature documents that young workers have the highest rates of injuries (Breslin and Smith, 2005; Estes et al., 2010; Guerin et al., 2020; NIOSH, 2023; Runyan and Zakocs, 2000; Salminen, 2004). Previous research offers several explanations, including younger workers' deficiencies in skills and experience, less understanding of work hazards, and lower compliance with safety rules (Arcury et al., 2020; Guerin et al., 2020; Gyekye and Salminen, 2009). Older workers display increased caution and confidence in their tasks, thereby minimizing the occurrence of unexpected situations that lead to injuries (Gherardi and Nicolini, 2002).

In our setting, older agricultural workers may be more aware of the risks associated in working during wildfire smoke events and may implement defensive measures to mitigate exposure. For instance, older agricultural workers may be more inclined to adopt protective measures, such as avoiding work or using masks on smoky days. Thus results might be driven by differential levels of smoke exposure across age groups. Differential effects may also be driven by survivorship bias. Older agricultural workers in the market are often the healthiest and most cautious individuals—the ones who have avoided injury—while other workers have transitioned out of agricultural work (MacKenzie et al., 1998).

These findings are consistent with previous research examining the impact of extreme temperatures on worker injuries by age, as documented in Park et al. (2021) using WCIS data. Specifically, Park et al. (2021) observe that individuals in their 20s experience additional injury risk of 7.7% on days exceeding 90°F, whereas those aged 60 and above exhibit additional risk of just 2.5%, a statistically insignificant result.

2.6. Discussion and Conclusion

We present novel evidence of the adverse impact of wildfire smoke on agricultural workers, drawing from extensive injury-claims data spanning 2007 to 2021 from the largest US workers'-compensation system in the state with the most agricultural workers. We quantify the direct costs of wildfire smoke's effects on agricultural workers' health in California. Wildfires led to roughly 282 additional injuries in 2020 relative to a hypothetical baseline without wildfires. To give a sense of the magnitude of this effect, this is about 1.4% of all reported agricultural-worker injuries in the same year. The average cost of an injury reported to the workers'-compensation system is about $49,520 in 2024 (NSC, 2022).[2] This means the annual direct costs of wildfire smoke on agricultural workers is about $14 million in California.

The number and size of 2020 fires were unusually large, which may make it difficult to generalize results to earlier years. However, if we consider the rapidly increasing number and intensity of fires, and given the expected increases in wildfires due to climate change in the future, estimates may be relevant for thinking about the future direct costs of wildfire smoke on agricultural workers' health. By the end of the century, the likelihood of wildfire events is projected to increase by a factor of 1.31 to 1.57 (Sullivan et al., 2022). This implies direct costs in the range of $18–$21 million in California, absent policy changes.

There are many reasons to think that direct costs underestimate the true costs associated with wildfire smoke. First, our estimates only include direct medical costs, and do not include pain and suffering as well as long run costs, which are almost certainly substantial. Second, there can be indirect costs of wildfire-induced worker injuries. The health risks from wildfire could drive up wages for agricultural workers as workers substitute to other occupations, e.g. construction or food services (Charlton et al., 2021). In the face of ongoing labor shortages (Rutledge et al., 2019), this may reduce agricultural production (Rutledge and Mérel, 2023), leading to greater social costs in the future than current estimates suggest.

We find that the net effect of wildfire smoke exposure has an important and perhaps counterintuitive age gradient among agricultural workers. Previous research has predominantly focused on the impact of air pollution on vulnerable groups such as children and the elderly (Beatty and Shimshack, 2011, 2014; Chay and Greenstone, 2003; Currie and Neidell, 2005; Deryugina et al., 2019; Ebenstein et al., 2017; Knittel et al., 2016; Schlenker and Walker, 2016). Moreover, policy development has traditionally centered on protecting these groups from the adverse effects of air pollution (EPA, 2018). We provide novel evidence that younger agricultural workers are an important at-risk demographic in the context of occupational health and safety. Our findings suggest a need to include younger workers in policy development and a need for targeted educational initiatives to improve safety in smoky work environments.

Our findings have important implications for existing air-quality regulations and outdoor-worker protection policies, particularly in regions prone to wildfires such as California (Castle and Revesz, 2018; Council et al., 2009; McGartland et al., 2017). Almost all air-quality regulations and wildfire-smoke protection policies in the United States rely on predefined thresholds for air-pollutant exposure, which

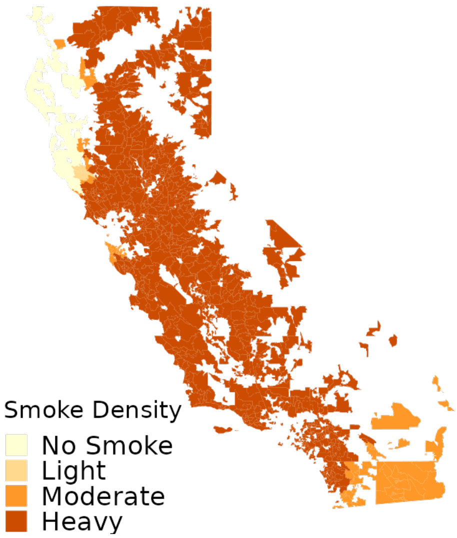
[2] We use 2021 injury cost information and the Consumer Price Index (CPI) inflation rate from 2021 to January 2024 to obtain an injury cost in 2024 dollars.

assume that exposure at levels below these thresholds poses no important health risks. However, our research calls these thresholds into question – we find economically important and statistically significant increases in injuries among agricultural workers, even at exposure levels below the existing policy thresholds. Further, current regulations seek to mitigate the effects of air pollution on respiratory and cardiovascular health. Our results contribute to a growing evidence base that smoke and air pollution more broadly also increase the risk of traumatic injuries, suggesting scope for broader worker health and safety policies.

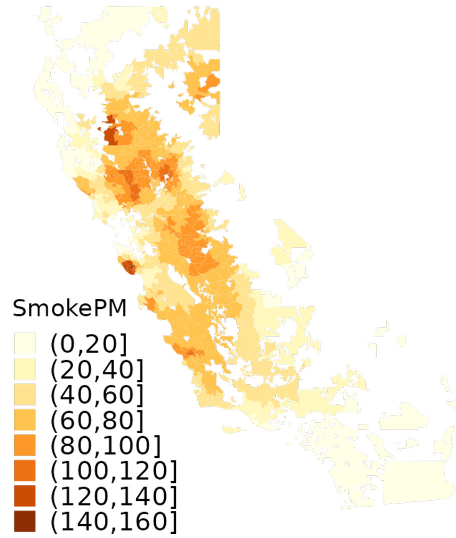
2.7. Appendix

FIGURE S2.1. Smoke, $PM_{2.5}$ and Injuries by Zip Code

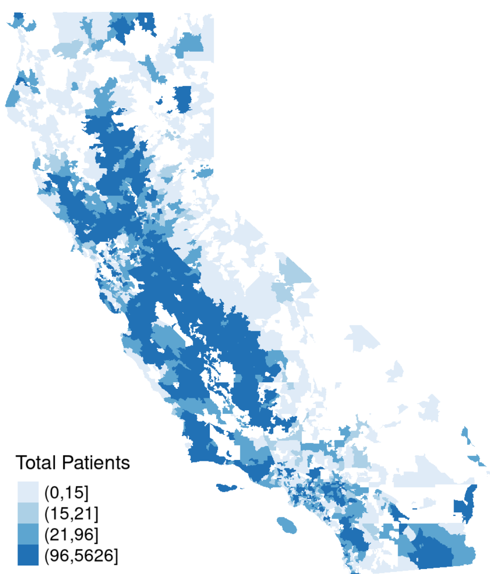
(a) Smoke



(b) SmokePM

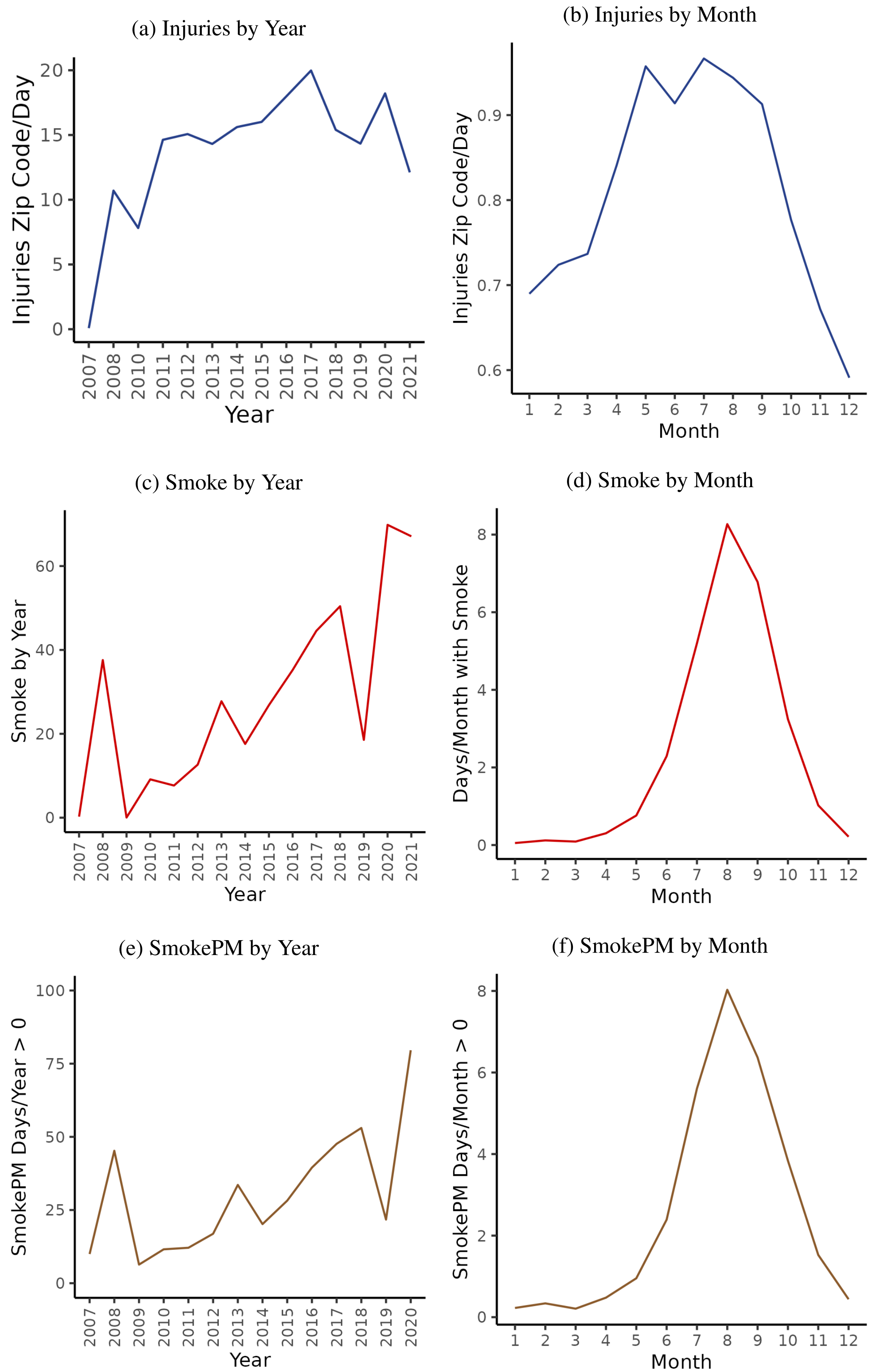


(c) Total Injuries



Notes: The panel (a) in figure S2.1 depicts geographical variation in the smoke density in August 20 in 2020 and panel (b) shows the variation in the $PM_{2.5}$ from smoke in the same date. Panel (c) presents the total number of injury claims in zip code with crop field from 2007 to 2021.

FIGURE S2.2. Temporal Variations in Smoke, $PM_{2.5}$ and Injuries



Notes: In figure S2.2, panels (a) and (b) display the average total number of injuries in a zip code per year and per month, respectively. Panels (c) and (d) illustrate the average number of days that each zip code experienced smoke per year and per month, respectively. Additionally, panels (e) and (f) depict the average number of days that each zip code experienced a SmokePM value exceeding 0 per year and per month, respectively.

TABLE S2.1. The Relationship between Traumatic Injury and Smoke and $PM_{2.5}$: OLS

	(1)	(2)	(3)	(4)	(5)
(A) Smoke					
Smoke	0.0055**	0.0025***	0.0048***	0.0016**	0.0024***
	(0.0022)	(0.0006)	(0.0013)	(0.0007)	(0.0006)
Dep. var. mean	0.0213	0.0213	0.0213	0.0213	0.0213
Control. mean	0.0205	0.0205	0.0205	0.0205	0.0205
Effect relative to mean, percent	26.97	12.03	23.42	7.876	11.46
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
R^2	0.00122	0.14125	0.13606	0.19676	0.14128
(B) SmokePM					
SmokePM	0.00022***	0.00007**	0.00019***	0.00007**	0.00006**
	(0.00007)	(0.00003)	(0.00004)	(0.00003)	(0.00003)
Dep. var. mean	0.0213	0.0213	0.0213	0.0213	0.0213
Control. mean	0.0204	0.0204	0.0204	0.0204	0.0204
Effect relative to mean, percent	1.051	0.3076	0.8870	0.3407	0.2888
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
R^2	0.00119	0.14124	0.13604	0.19675	0.14128
Weather Controls	✓		✓	✓	✓
Year x Month fixed effects		✓			✓
Zip x Year fixed effects		✓			✓
Year fixed effects			✓		
Zip x Month fixed effects			✓		
Year x Month x Zip fixed effects				✓	

Notes: Table S2.1 reports the results of equations 2.1 and 2.3 using the Ordinary Least Squares model instead of the Poisson model for both the Smoke and SmokePM variables. 'Dep.var.mean' represents the average number of traumatic injuries by zip code and day, while 'Control.mean' indicates the average number of traumatic injuries by zip code and day when there is no smoke or SmokePM (i.e., when SmokePM = 0).

TABLE S2.2. The Nonlinear Relationship between Traumatic Injury and Smoke

	(1)	(2)	(3)	(4)	(5)
Light	0.1671**	0.0696***	0.1383***	0.0610**	0.0727***
	(0.0628)	(0.0191)	(0.0303)	(0.0218)	(0.0200)
Moderate	0.2277*	0.0684**	0.1397**	0.0426	0.0733**
	(0.1109)	(0.0248)	(0.0509)	(0.0315)	(0.0270)
Heavy	0.3160*	0.1034	0.2933***	0.0810	0.1095
	(0.1568)	(0.0737)	(0.0901)	(0.0842)	(0.0741)
Dep. var. mean	0.0213	0.0213	0.0213	0.0213	0.0213
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
Weather Controls	✓		✓	✓	✓
Year x Month fixed effects		✓			✓
Zip x Year fixed effects		✓			✓
Year fixed effects			✓		
Zip x Month fixed effects			✓		
Year x Month x Zip fixed effects				✓	

Notes: Table S2.2 reports the results of equation 2.2 where the dependent variable is the number of traumatic injuries. 'Dep.var.mean' represents the average number of traumatic injuries by zip code and day. Standard error based on estimates clustered by zip code and year.

TABLE S2.3. The Nonlinear Relationship between Traumatic Injury and $PM_{2.5}$

	(1)	(2)	(3)	(4)	(5)
Low	0.3788***	0.0664***	0.1112***	0.0521**	0.0658***
	(0.0523)	(0.0159)	(0.0270)	(0.0187)	(0.0158)
Medium	0.4686***	0.0496	0.1917**	0.0242	0.0495
	(0.0903)	(0.0527)	(0.0798)	(0.0538)	(0.0508)
High	0.5317***	0.1327**	0.3338***	0.1345*	0.1336**
	(0.1671)	(0.0587)	(0.0802)	(0.0632)	(0.0580)
Dep. var. mean	0.0213	0.0213	0.0213	0.0213	0.0213
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
Weather Controls	✓		✓	✓	✓
Year x Month fixed effects		✓			✓
Zip x Year fixed effects		✓			✓
Year fixed effects			✓		
Zip x Month fixed effects			✓		
Year x Month x Zip fixed effects				✓	

Notes: Table S2.3 reports the results of equation 2.4 where the dependent variable is the number of traumatic injuries. 'Dep.var.mean' represents the average number of traumatic injuries by zip code and day. Standard error based on estimates clustered by zip code and year.

TABLE S2.4. Nonlinear Relationship between Respiratory & Cardiovascular Injury, Smoke, and $PM_{2.5}$

	(1)	(2)	(3)	(4)	(5)
(A) Smoke					
Light	0.3465**	0.0723	0.0251	0.0469	0.0626
	(0.1176)	(0.1188)	(0.0931)	(0.1424)	(0.1192)
Moderate	0.6052*	0.3408	0.2322	0.2908	0.3316
	(0.3398)	(0.2691)	(0.3533)	(0.3194)	(0.2683)
Heavy	0.8133**	0.5147	0.5272	0.4060	0.4973
	(0.2740)	(0.4290)	(0.3310)	(0.4802)	(0.4351)
Dep. var. mean	0.0002	0.0002	0.0002	0.0002	0.0002
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
(B) SmokePM					
Low	0.5959***	0.2392	0.1885	0.2303	0.2304
	(0.1494)	(0.1622)	(0.1514)	(0.1935)	(0.1614)
Medium	0.5432***	0.2281	0.1661	0.1396	0.2138
	(0.1440)	(0.2079)	(0.1034)	(0.2070)	(0.2069)
High	0.7125**	0.4330	0.3551	0.2704	0.3979
	(0.2752)	(0.2476)	(0.4004)	(0.2614)	(0.2316)
Dep. var. mean	0.0002	0.0002	0.0002	0.0002	0.0002
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
Weather Controls	✓		✓	✓	✓
Year x Month fixed effects		✓			✓
Zip x Year fixed effects		✓			✓
Year fixed effects			✓		
Zip x Month fixed effects			✓		
Year x Month x Zip fixed effects				✓	

Notes: Table S2.4 reports the results of equations 2.1 and 2.3 where the dependent variable is the number of respiratory and cardiovascular injuries. 'Dep.var.mean' represents the average number of respiratory and cardiovascular injuries by zip code and day. Standard error based on estimates clustered by zip code and year.

TABLE S2.5. The Relationship between Injury, Smoke, and $PM_{2.5}$: Overall Injury

	(1)	(2)	(3)	(4)	(5)
(A) Smoke					
Smoke	0.1977**	0.0772***	0.1511***	0.0582**	0.0753***
	(0.0698)	(0.0174)	(0.0344)	(0.0207)	(0.0180)
Dep. var. mean	0.0270	0.0270	0.0270	0.0270	0.0270
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
(B) SmokePM					
SmokePM	0.0083***	0.0026***	0.0054***	0.0023***	0.0025***
	(0.0011)	(0.0007)	(0.0011)	(0.0007)	(0.0007)
Dep. var. mean	0.0270	0.0270	0.0270	0.0270	0.0270
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
Weather Controls	✓		✓	✓	✓
Year x Month fixed effects		✓			✓
Zip x Year fixed effects		✓			✓
Year fixed effects			✓		
Zip x Month fixed effects			✓		
Year x Month x Zip fixed effects				✓	

Notes: Table S2.5 reports the results of equations 2.1 and 2.3 where the dependent variable is the overall number of injuries. 'Dep.var.mean' represents the average number of injuries by zip code and day. Standard error based on estimates clustered by zip code and year. * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

TABLE S2.6. Placebo Test

	Hernia (1)	Mental Disorder (2)	Hernia (3)	Mental Disorder (4)
(A) Smoke				
Light	0.0361	-0.0556		
	(0.1189)	(0.2140)		
Moderate	-0.2274*	0.0785		
	(0.1210)	(0.2976)		
Heavy	-0.0356	-0.6970		
	(0.1770)	(0.5536)		
Dep. var. mean	0.0002	0.0001		
Observations	8,657,654	8,657,654		
(B) SmokePM				
Low			-0.1469	0.1525
			(0.0927)	(0.1820)
Medium			0.3322	-0.6103
			(0.2928)	(0.6897)
High			-0.1694	0.2005
			(0.2920)	(0.3377)
Dep. var. mean			0.0002	0.0001
Observations			8,657,654	8,657,654
Weather Controls	✓	✓	✓	✓
Year x Month fixed effects	✓	✓	✓	✓
Zip x Year fixed effects	✓	✓	✓	✓

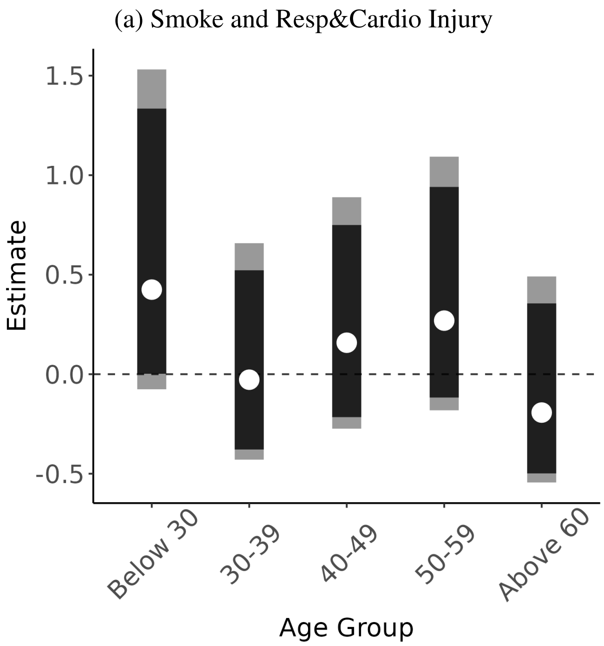
Notes: Table S2.6 presents the results of equations 2.1 and 2.3, with the dependent variable being the number of hernia claims for columns (1) and (3), and mental disorder claims for columns (2) and (4). 'Dep.var.mean' represents the average number of hernia and mental disorder claims by zip code and day. Standard errors are estimated using clustering by zip code and year.

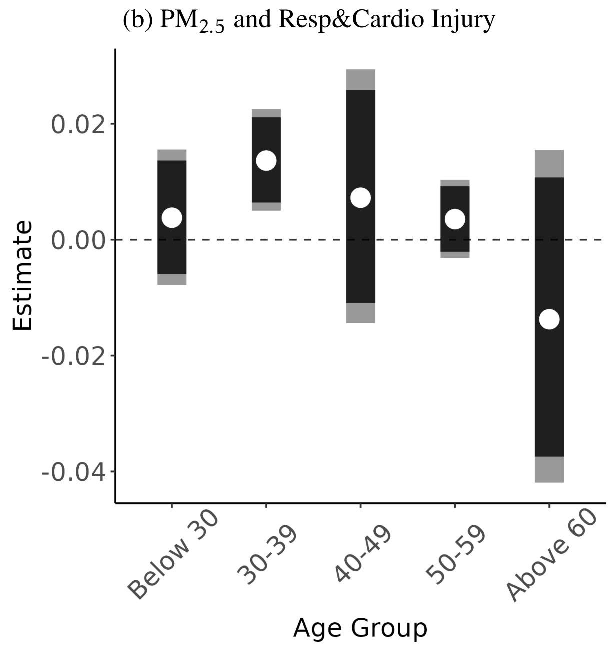
TABLE S2.7. The Relationship between Injury, Smoke, and $PM_{2.5}$ by Age

	Below 30 (1)	30-39 (2)	40-49 (3)	50-59 (4)	Above 60 (5)
Traumatic					
(A) Smoke					
Smoke	0.1066***	0.0843***	0.0615***	0.0372	0.0767**
	(0.0310)	(0.0184)	(0.0199)	(0.0220)	(0.0350)
Dep. var. mean	0.0070	0.0067	0.0063	0.0049	0.0020
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
(B) SmokePM					
SmokePM	0.0035***	0.0019*	0.0022**	0.0019	0.0027
	(0.0006)	(0.0009)	(0.0007)	(0.0012)	(0.0020)
Dep. var. mean	0.0070	0.0067	0.0063	0.0049	0.0020
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
Respiratory & Cardiovascular					
(A) Smoke					
Smoke	0.4249	-0.0277	0.1582	0.2692	-0.1929
	(0.2570)	(0.2722)	(0.2439)	(0.2395)	(0.3022)
Dep. var. mean	0.00004	0.00004	0.00004	0.00003	0.00002
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
(B) SmokePM					
SmokePM	0.0038	0.0136***	0.0072	0.0035	-0.0137
	(0.0059)	(0.0044)	(0.0111)	(0.0034)	(0.0148)
Dep. var. mean	0.00004	0.00004	0.00004	0.00003	0.00002
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
Weather Controls	✓	✓	✓	✓	✓
Year x Month fixed effects	✓	✓	✓	✓	✓
Zip x Year fixed effects	✓	✓	✓	✓	✓

Notes: Table 3.5 reports the results of equations 2.1 and 2.3 by age group and injury type. 'Dep.var.mean' shows the average number of injuries by zip code and day for each age group.

FIGURE S2.3. The Relationship between Injuries, Smoke, and $PM_{2.5}$ by Age: : Respiratory and Cardiovascular Injuries





Notes: The figure displays the regression results from equations 2.1 and 2.3 categorized by age groups. The age groups are delineated as follows: "Below 30" represents workers aged under 30, "30-39" between 30 and 39, "40-49" between 40 and 49, "50-59" between 50 and 59, and "Above 60" aged 60 and above. Panel (a) depicts the result for smoke analysis, and panel (b) shows the result for $PM_{2.5}$ analysis.

2.7.1. Robustness.

2.7.1.1. *Cluster.*

TABLE S2.8. Robustness of Main Estimates to Clustering Choices

	(1)	(2)	(3)
(A) Smoke			
Smoke	0.0769***	0.0769***	0.0769***
	(0.0152)	(0.0214)	(0.0207)
Dep. var. mean	0.0213	0.0213	0.0213
Observations	8,657,654	8,657,654	8,657,654
(B) SmokePM			
SmokePM	0.0024**	0.0024**	0.0024***
	(0.0010)	(0.0011)	(0.0006)
Dep. var. mean	0.0213	0.0213	0.0213
Standard-Errors	Zip & Year & Month	County & Date	County & Year
Observations	8,657,654	8,657,654	8,657,654
Weather Controls	✓	✓	✓
Year x Month fixed effects	✓	✓	✓
Zip x Year fixed effects	✓	✓	✓

Notes: Table S2.8 reports the results of equations 2.1 and 2.3 while we cluster the standard errors using different cluster levels (Standard-Errors) for both the smoke and SmokePM variables. 'Dep.var.mean' shows the average number of traumatic injuries by zip code and day.

TABLE S2.9. The Relationship between Injury and Smoke: Geographical Coverage

	(1)	(2)	(3)	(4)	(5)
Smoke	0.1728**	0.0644**	0.1648***	0.0515*	0.0687**
	(0.0791)	(0.0245)	(0.0468)	(0.0264)	(0.0250)
Dep. var. mean	0.0213	0.0213	0.0213	0.0213	0.0213
Observations	8,657,654	8,657,654	8,657,654	8,657,654	8,657,654
Weather Controls	✓		✓	✓	✓
Year x Month fixed effects		✓			✓
Zip x Year fixed effects		✓			✓
Year fixed effects			✓		
Zip x Month fixed effects			✓		
Year x Month x Zip fixed effects				✓	

Notes: Table S2.9 presents the results of equation 2.1, where a zip code is considered covered with smoke only if it fully covers the zip code. 'Dep.var.mean' shows the average number of traumatic injuries by zip code and day.

2.7.1.2. *Smoke Spatial Coverage.*

TABLE S2.10. Relationship between Injury and Smoke with Wind Controls

	(1)	(2)	(3)
Smoke	0.0768***	0.0772***	0.0769***
	(0.0217)	(0.0217)	(0.0217)
Dep. var. mean	0.0213	0.0213	0.0213
Observations	8,657,654	8,657,654	8,657,654
Wind Direction		✓	✓
Wind Speed	✓		✓
Year x Month fixed effects	✓	✓	✓
Zip x Year fixed effects	✓	✓	✓

Notes: Table S2.10 reports the results of equation 2.1, where the dependent variable is the number of traumatic injuries. Additionally, wind direction and wind speed variables are included as controls. 'Dep.var.mean' represents the average number of traumatic injuries by zip code and day. Standard errors are estimated using clustering by zip code and year.

2.7.1.3. *Weather Control.*

TABLE S2.11. Rolling Window Estimates

	3 Days (1)	4 Days (2)	5 Days (3)
SmokePM	0.0024***	0.0024***	0.0026***
	(0.0005)	(0.0006)	(0.0005)
Dep. var. mean	0.0213	0.0213	0.0213
Observations	8,657,654	8,657,654	8,657,654
Weather Controls	✓	✓	✓
Year x Month fixed effects	✓	✓	✓
Zip x Year fixed effects	✓	✓	✓

Notes: Table S2.11 reports the results of equation 2.3 where the dependent variable, injury counts, is averaged over a rolling window of three, four, and five consecutive days for columns (1)-(3), respectively.

CHAPTER 3

Agricultural Burning and Agricultural-Worker Injury

3.1. Introduction

Agricultural burning produces harmful air pollutants such as $PM_{2.5}$ that have detrimental health impacts (CARB, 2021b; Pope III and Dockery, 2006). The size of the area burned by agricultural fires is comparable to 43% of the area burned by wildfires (McCarty et al., 2009). Given they work outdoors near burn sites, agricultural workers are disproportionately exposed to agricultural burning. However, research on the effect of agricultural burning on agricultural workers' health is limited (Pennington et al., 2023). Prior work focuses on the effects of agricultural or biomass burning on air quality (Guo, 2021) and broad health impacts in developing countries (He et al., 2020; Pullabhotla et al., 2023; Rangel and Vogl, 2019; Zivin et al., 2020). The effects of such burning in the U.S. remain understudied. California burns around 205,000 acres of crop residue annually, contributing to the release of an estimated six tons of $PM_{2.5}$ (CARB, 2021c; Pouliot et al., 2017). We conduct the first quasi-experimental investigation of the effects of agricultural burning on agricultural worker injuries in California.

The key empirical challenge involves distinguishing between the health consequences of agricultural fires and the effects of other socioeconomic variables such as economic activity linked to fire occurrences (Pullabhotla et al., 2023). Identifying the health consequences of agricultural fires requires separating the effects of pollution produced from any potential health or economic advantages associated with burning. We use daily shifts in wind direction as a source of plausibly exogenous variation to estimate the impacts on worker injuries. We compare the number of injuries in a zip code located upwind versus downwind of agricultural burning sites within a 30-kilometer radius.

We use administrative burn permit data from seven key air districts in California, encompassing significant agricultural burning regions. We gather available permit data from California air districts that provide both daily and geographical information. Specifically, seven districts include the San Joaquin Valley, which is responsible for 36% of $PM_{2.5}$ emissions from agricultural burning in California, the highest in the state. Our permit data also includes part of the Sacramento Valley, which emits another 30% of $PM_{2.5}$ from burning, specifically the Feather River and Sacramento Metro districts (CARB, 2021c). In California, agricultural burning is strictly regulated and permitted only to permit holders. This comprehensive permit data ensures a more accurate representation of agricultural burning practices and their impacts on air quality and health outcomes. This approach allows us to precisely capture the day and location of agricultural burning activities. In contrast, many studies primarily rely on satellite imagery for defining agricultural burning sites (Ferguson, 2023; Pennington et al., 2023; Pullabhotla et al., 2023; Rangel and Vogl, 2019; Zivin et al., 2020). However, satellite imagery is better suited to capturing large-scale agricultural fires. Compared to the actual burning events recorded in our permit data, satellite imagery identifies only a small share of burnings.

To measure the health outcomes of agricultural workers, we leverage compensation claims data from California's Workers' Compensation Information System (CA WCIS) spanning 2000 to 2021. A unique feature of worker's compensation data is that it includes a significant number of undocumented farmworkers, a demographic traditionally challenging to monitor and survey. Given that roughly half of the U.S. farmworkers are undocumented, the workers' compensation data offers a novel approach to studying the effects of agricultural burning on agricultural workers' health.

We find that $PM_{2.5}$ levels are higher in the downwind region of the agricultural burning sites. We also find that exposure to smoke from agricultural burning leads to an increase in injuries among agricultural workers. Specifically, one additional agricultural fire leads to 0.56 additional injuries per thousand workers downwind of fires. The impact on farmworker injuries is larger when agricultural burnings occur over multiple days. Finally, we find that the effect of smoke is larger for older workers compared to younger workers.

This paper makes contributions to three related literature. We contribute to the large body of studies examining the specific emissions sources of air pollution that cause health damage. Recent examples of such research include investigations into the health effects of air pollution from school buses (Beatty and Shimshack, 2011), airplanes (Schlenker and Walker, 2016), wildfire smoke (Heft-Neal et al., 2023c), and maritime activities (Hansen-Lewis and Marcus, 2022). Notably, Rangel and Vogl (2019) find that prenatal exposure to smoke from sugarcane harvest fires negatively impacts birth health outcomes in Brazil. Our study complements these studies by offering new evidence regarding the health implications of agricultural burning on workers' health in the U.S. context.

Second, we contribute to the large agricultural labor literature by studying the health and well-being of agricultural workers. While previous studies have focused on aspects such as labor productivity, labor supply, immigration, and income (Hamilton et al., 2022; Hertz and Zahniser, 2013; Kostandini et al., 2014; Richards, 2020), the health of agricultural workers remains understudied. The existing literature on this topic has focused on the health impacts of pesticide use (Crissman et al., 1994; McCauley et al., 2006; Sunding and Zivin, 2000). We expand this literature by providing evidence on the effects of another important agricultural practice, agricultural burning, on agricultural worker's health and well-being.

Lastly, we add to the literature studying the effect of environmental conditions on marginalized groups (Chay and Greenstone, 2003; Currie and Walker, 2011; Hsiang et al., 2019; Jayachandran, 2009). Previous studies establish that air pollution tends to have larger effects in economically disadvantaged areas (Jayachandran, 2009), African-American communities (Currie and Walker, 2011), and developing countries (Arceo et al., 2016). Our research builds on earlier work by investigating the health outcomes of one of the most marginalized groups in society – agricultural workers, characterized by low income, education levels, and limited access to social safety nets (Hill, 2016).

Our findings have several important policy implications. First, our results offer valuable insights into discussions of a phase-out policy aimed at gradually eliminating agricultural burning by providing rigorous evidence of the detrimental health impact of burning on agricultural workers. The San Joaquin Valley in California, a region where agricultural burning is common, experienced several postponements of the phase-out policy for agricultural burning (Ferguson, 2023). This delay was allowed based on the rationale that agricultural burning is the most cost-effective option, and the economic burden of choosing alternatives would be too high. By highlighting the potential health risks associated with agricultural burning, our study's findings offer evidence to reconsider the validity of this claim.

More broadly, our findings suggest that regulating agricultural burning has important health benefits. While California maintains stringent regulations on agricultural burning permits, numerous other states, including Texas, lack comparable measures (Treadwell and Lashmet, 2021). The large impact of agricultural burning on the health of agricultural workers implies that health costs arising from agricultural burning across the nation could be significant. It also suggests that implementing protective measures for workers, such as wearing masks, could be a cost-effective investment with significant health benefits.

The remaining sections of the paper are structured as outlined below. Section II provides a concise overview of agricultural burning along with an explanation of the relationship between $PM_{2.5}$ and worker injuries. Section III introduces the sources of our data and summary statistics of the key variables. In Section IV, we detail our empirical approach. The main findings are presented in Section V, and the paper concludes with Section VI, offering final remarks.

3.2. Background

3.2.1. Agricultural Burning. The open burning of agricultural fields is a widespread practice employed for clearing crop residue post-harvest, preparing fields for planting, and pest and weed control (Andreae, 1991; Ferguson, 2023; Jenkins et al., 1992). Given this, most agricultural burning takes place during the post-harvest season in California, which spans September to the pre-planting season around April. Agricultural burning is considered a quick and cost-effective agricultural practice (Ferguson, 2023).

Agricultural burning is an important but underestimated source of air pollution. In the U.S. alone, approximately 3 to 5.8 million acres each year are burned (Pouliot et al., 2017). This practice directly affects approximately 15.5 million people across the U.S., exposing them to the resulting smoke (McCarty, 2011).

California burns the largest amount of crop residue annually, approximately 205,000 acres, contributing to the release of an estimated six tons of $PM_{2.5}$ (CARB, 2021c; Pouliot et al., 2017). The effect of agricultural burning on local air pollution is large. The top five cities (e.g., Bakersfield, Visalia, Fresno, Madera, and Hanford) listed as the worst for year-round particle pollution in the U.S. were in San Joaquin Valley in 2024 (ALA, 2023), where most agricultural burning occurs in California.

In California, agricultural burning is subject to stringent regulations. Individuals must obtain a permit before burning agricultural waste. Violating this requirement carries significant penalties, with fines of up to $50,000 per day. It's worth noting that not all states in the U.S. have a similar permitting system for agricultural burning. For instance, Texas does not require permits for agricultural burning (Treadwell and Lashmet, 2021), despite significant burning of crop residues (McCarty et al., 2009; Pouliot et al., 2017).

3.2.2. Health Effects of Agricultural Burning. Concerns about the health consequences of agricultural burning have long been an issue in California (Jenkins et al., 1991). The smoke produced from agricultural burning contains a complex mix of chemical compounds (McCarty, 2011) including $PM_{2.5}$ which is known as a main concern from biomass burning (EPA, 2021a). Acute and chronic exposures to these pollutants have the potential to cause adverse health effects (Pope III and Dockery, 2006). The compounds found in $PM_{2.5}$ from biomass burning, such as potassium, organic carbon, and elemental carbon have a greater health impact, as measured by increases in emergency room admissions, relative to $PM_{2.5}$ from other sources (Krall et al., 2017; Sarnat et al., 2008).

Emissions from agricultural burning not only increase the risk of respiratory illnesses but may also increase the occurrence of traumatic injuries, especially in the context of one of the most dangerous occupations—agricultural work (Beatty and Lee, 2023, 2024a). Agricultural work often involves dangerous tasks such as operating heavy machinery, cutting vegetables, and climbing ladders (NIFA, 2022). In hazardous environments, even a minor lapse of attention or a small mistake can result in significant injuries (Sunyer et al., 2017).

Given a risky work environment, exposure to $PM_{2.5}$ is a contributing factor that can compromise both productivity and cognitive performance, elevating the susceptibility to traumatic injuries. Research highlights the adverse effects of $PM_{2.5}$ exposure on the productivity of various occupational groups, including outdoor agricultural workers and professionals in sectors such as agriculture, call centers, and investment (Chang et al., 2016, 2019; Heyes et al., 2016; Zivin and Neidell, 2012). Moreover, existing literature finds a negative impact of $PM_{2.5}$ on cognitive performance, leading to lower test scores (Ebenstein et al., 2016; Gilraine, 2023; Lai et al., 2022; Wen and Burke, 2022).

Second, $PM_{2.5}$ exposure can lead to stress-related behavioral changes. Air pollution, specifically $PM_{2.5}$, can elevate stress-related hormones, inducing heightened impatience, aggression, and risk-taking behavior. Studies have linked acute air pollution exposure to increased levels of stress-related hormones such as cortisol, cortisone, and epinephrine (Li et al., 2017; Miller et al., 2016; Snow et al., 2017). Elevated stress hormone levels may lead to changes in work behavior, including heightened impatience (Riis-Vestergaard et al., 2018). Similarly, air pollution has been correlated with elevated serotonin levels, potentially resulting in increased aggression and changes in risk-taking tendencies (Murphy et al., 2013). This behavioral change may cause workers to forego protective gear and avoid necessary but complex safety procedures, increasing the likelihood of traumatic injuries.

Another mechanism leading to an increased risk of traumatic injuries involves smoke-related discomforts, such as blurred vision and itchy eyes (Holm et al., 2021; Jaiswal et al., 2022). Research has shown that wildfire smoke can lead to ocular symptoms such as irritation, grittiness, burning sensation, excessive watering, and dryness, affecting both the general population and firefighters (Howard et al., 2020; Jaiswal et al., 2022; Kunzli et al., 2006). The distraction arising from the discomfort associated with these vision issues can further contribute to injuries, especially when combined with the inherent dangers present in agricultural work environments.

A growing body of research provides empirical evidence of these mechanisms by studying the impact of adverse environmental conditions, such as air pollution and extreme temperatures, on traumatic injuries, particularly in the context of workplace injuries (Akesaka and Shigeoka, 2023; Dillender, 2021; Ireland et al., 2023; Park et al., 2021). Ireland et al. (2023), using occupational health claims from various job sectors, report a significant rise in traumatic workplace injuries during extreme temperatures compared to mild conditions. Similarly, Akesaka and Shigeoka (2023) find a correlation between elevated daily pollen counts and increased incidence of occupational injuries. Using workers' compensation data of agricultural workers in California, Beatty and Lee (2023) find that being exposed to wildfire smoke increases traumatic injuries significantly.

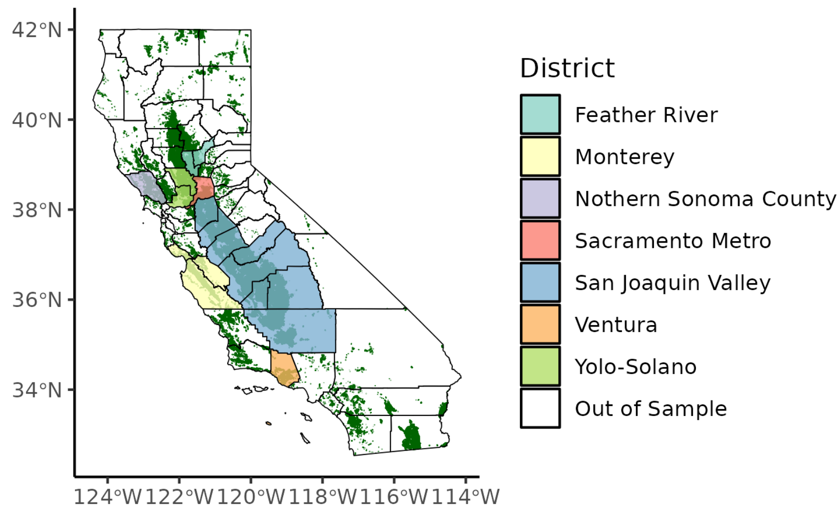
3.3. Data

To investigate how agricultural burning affects injuries among agricultural workers, we use data from California's Workers' Compensation Information System (CA WCIS). We merge this injury data with burning permit information from seven air districts in California and $PM_{2.5}$ data sourced from the U.S. Socioeconomic Data and Applications Center (SEDAC) of NASA (Wei et al., 2022). Additionally, we incorporate weather data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) (PRISM, 2021). This section outlines our procedure for constructing the data and sample.

3.3.1. Agricultural Burning Permits. We collect data from each of California's local air districts that report the date and location of the burning sites. We use data from seven major agricultural burning districts: Feather River Air Quality Management District (AQMD), Monterey Bay Air Resources District, Northern

Sonoma County Air Pollution Control District (APCD), Sacramento Metro AQMD, San Joaquin Valley APCD, Ventura County APCD, and Yolo-Solano AQMD. Particularly, San Joaquin Valley is responsible for 36% of $PM_{2.5}$ emissions from agricultural burning in California, the highest in the state (CARB, 2021c). The Feather River and Sacramento Metro districts are part of the Sacramento Valley that emit another 30% of $PM_{2.5}$ from agricultural burning.

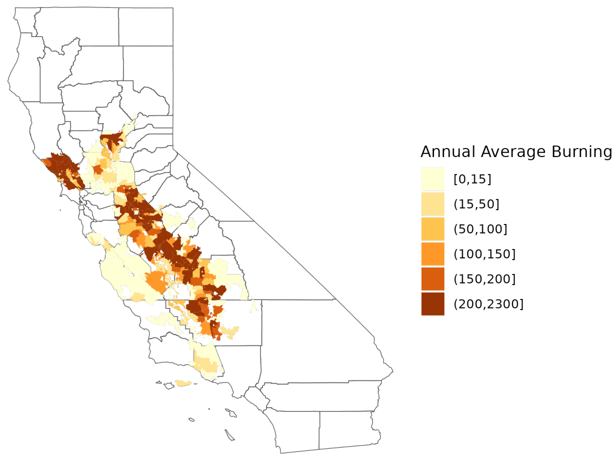
FIGURE 3.1. Air District and Agricultural Fields in CA



Notes: Figure 3.1 displays the counties included in each air district, with all crop fields in California plotted in dark green for reference.

Figure 3.1 illustrates the geographical distribution of counties within each air district and highlights crop fields in California in dark green dots. Our sample contains eighteen counties: Fresno, Kern, Kings, Madera, Merced, Monterey, Sacramento, San Benito, San Joaquin, Santa Cruz, Solano, Sonoma, Stanislaus, Sutter, Tulare, Ventura, Yolo, and Yuba. The seven air districts encompass a significant portion of California's crop fields. Notably, the San Joaquin Valley APCD, depicted in the figure, includes eight counties, encompassing the major central agricultural regions in California.

FIGURE 3.2. Agricultural Burning by Zip Code



Notes: Figure 3.2 presents the annual average number of agricultural burning by zip code.

Figure 3.2 displays the annual average number of agricultural burnings by zip code, highlighting considerable variation across the state. While the San Joaquin Valley tends to experience the most agricultural burning, there is also significant variation in the frequency of burning within the San Joaquin Valley.

Because each air district has different data management systems, the years for which permit data are available vary across districts. Table S3.1 in the Appendix provides detailed information on the available time period for each district. The San Joaquin Valley and Sacramento Metro districts cover the full period from 2000 to 2021 and Ventura Air District covers the shortest for the period between 2017 and 2021.

The geocoding of burns differs across air districts with some districts providing the precise latitude and longitude while other districts provide only addresses. We use Google Maps' location information to match the address details and pinpoint the location where the burning occurred. To add further precision to the matched locations, we additionally integrate the burning locations with a map containing all the different California crop field boundaries from the California Department of Water Resources (LandIQ, 2021). The resulting data consists of the locations of agricultural fires that occurred within crop fields.

Prior research relies predominantly on remote-sensing satellite imagery to define agricultural or biomass-burning sites (Ferguson, 2023; Pennington et al., 2023; Pullabhotla et al., 2023; Rangel and Vogl, 2019; Zivin et al., 2020). However, this method has limitations as it primarily captures large-scale agricultural burning. In our sample, only 2% of burnings were detected by satellite imagery in the San Joaquin Valley when compared to our permit data. Notably, the average quantity of tons burned per agricultural burning identified through satellite imagery was approximately 260 tons, 14 times larger than the average tons burned recorded in the permit data.

The study by Kamai et al. (2023) on the impact of agricultural burning on children's respiratory health uses permit data, but only from a single air district, Imperial Valley, over four years. Our data is more comprehensive. We collect burning permits from every available air district in California (seven districts) with permit records as of 2023, providing daily burning location information spanning up to 22 years. This method ensures greater generalizability of our findings and allows for a sufficiently large sample size to thoroughly investigate the relationship between burning and injuries.

3.3.2. California's Workers' Compensation Information System. We obtain data on injuries among agricultural workers from California's Workers' Compensation Information System (CA WCIS) for the period 2000 to 2021. WCIS provides individual and date-level injury details along with information about the worksite where the injury occurred. We aggregate individual injury records to the zip code and day level.

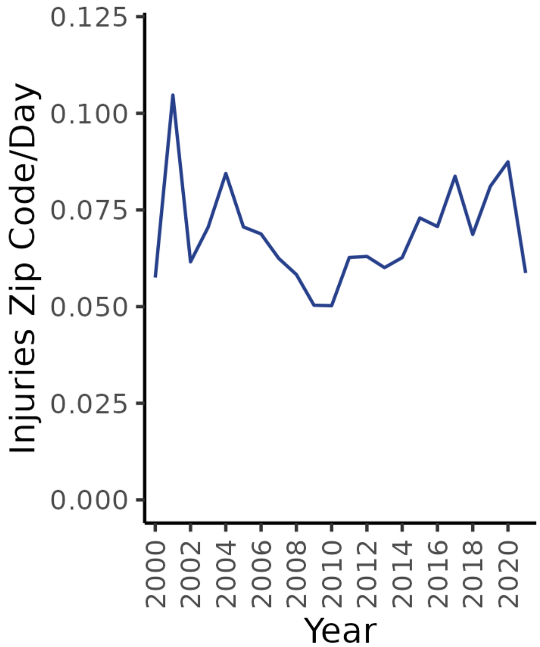
Workers' compensation claims data is unique for its detailed information on workers' occupations, in contrast to other data on health outcomes such as emergency department visit data. The presence of occupational information in the CA WCIS data enables us to specifically study the effects of injuries within the agricultural worker population who are more directly exposed to the effects of agricultural burning than the general population.

Another advantage of the CA WCIS data is it is comprehensive. This data provides extensive information on workplace injuries, following California law that mandates employers to offer worker's compensation insurance regardless of their legal status (DWC, 2020). Of particular importance, the data includes many undocumented farmworkers, a demographic that is typically challenging to monitor and survey. Over the last decade, undocumented workers made up roughly 50% of California's farm labor force (Martin, 2015).

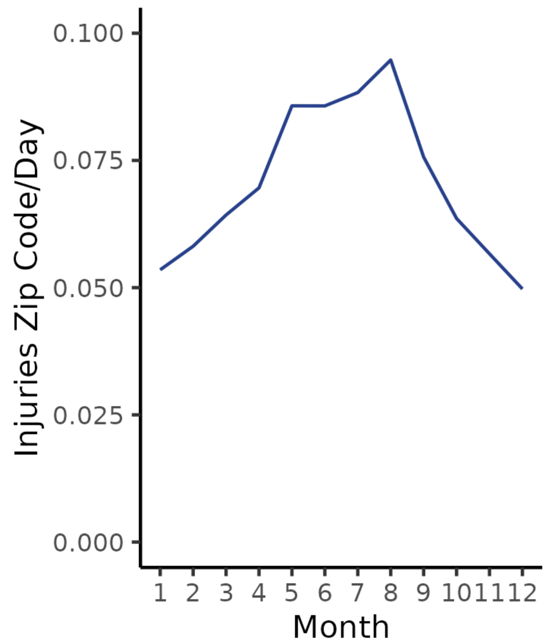
Another notable aspect of the CA WCIS data is its lower reporting threshold compared to workers' compensation data from other regions. For instance, data from other states often include only cases involving worker fatalities or injuries to three or more workers (Park et al., 2021). Moreover, datasets from other states frequently present highly aggregated data categorized by industry or state. In contrast, CA WCIS data provides individual and daily-level information on worker injuries, enabling us to conduct detailed heterogeneity analyses.

FIGURE 3.3. Temporal and Spatial Variations in Worker Injuries

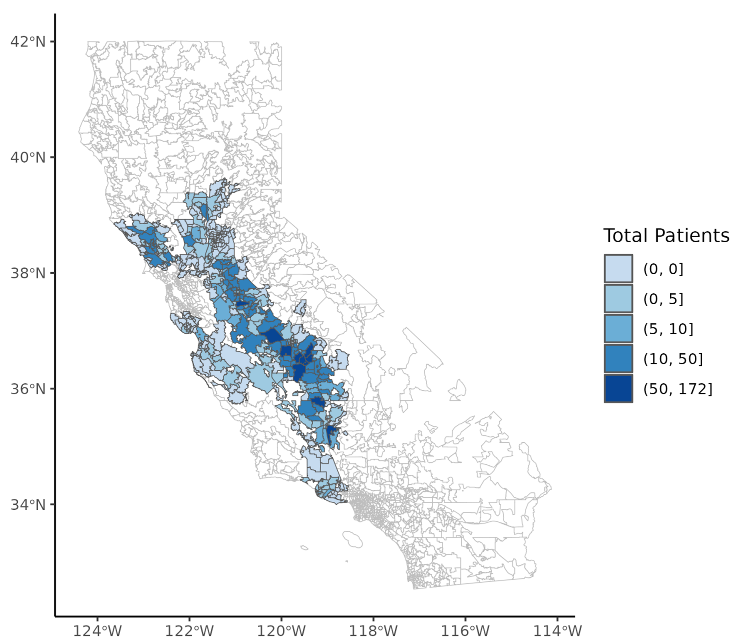
(a) Injuries by Year



(b) Injuries by Month



(c) Total Injuries by Zip Code



Notes: Panel (a) and (b) depict the average number of injuries by zip code per year and month. Panel (c) presents the annual average total count of injury claims per zip code in our sample from 2000 to 2021.

Figure 3.3 highlights temporal and geographical patterns of injuries in our data. Panels (a) and (b) show the average number of injuries per year and by month-of-year. Injuries typically occur between June and September. There is no evident trend over the sample period. Panel (c) shows the spatial distribution of injury claims in our sample. Injuries roughly mirror the distribution of agriculture and the resulting burning in the state.

3.3.3. Weather. For wind direction and wind speed, we use data from Gridded Surface Meteorological (gridMET) (Abatzoglou, 2013). gridMET data record the daily wind direction and wind speed at a 4 x 4 km^2 grid. We also include daily maximum temperature and daily total precipitation as controls to deal with potential confounding from environmental factors that covary with air pollution. The Parameter-elevation Regressions on Independent Slopes Model (PRISM) Climate Group provides daily records at a 4 x 4 km^2 resolution (PRISM, 2021). We aggregate grids into zip code and date levels to match the injury data. If more than one grid covers a zip code, we average the daily weather values by zip code.

3.3.4. $PM_{2.5}$. To estimate $PM_{2.5}$ levels downwind of agricultural burning sites, we gather data on daily $PM_{2.5}$ concentrations. Traditional methods for data construction in urban settings, such as assigning values from the nearest monitoring station or using inverse distance weighting, are impractical due to the limited availability of $PM_{2.5}$ monitors in rural areas. Interpolating values from far-way monitors may introduce large noises on $PM_{2.5}$ levels.

To address this challenge, we use data provided by the U.S. Socioeconomic Data and Applications Center (SEDAC) of the National Aeronautics and Space Administration (NASA) (Wei et al., 2022). This dataset leverages ensemble predictions from three machine-learning models (Random Forest, Gradient Boosting, and Neural Network) to estimate daily concentrations at the centroids of 1 x 1 km^2 grid cells across the U.S. between 2000 and 2016. The predictors employed include air monitoring data, satellite aerosol optical depth, meteorological conditions, chemical transport model simulations, and land-use variables. The authors of this dataset recommend its use, particularly for research focused on under-represented rural populations, given the scarcity of air monitoring sites in rural areas (Wei et al., 2022), aligning with the focus of our research. The dataset is provided in a zip code and daily level by aggregating the grids.

We combine our burning permit data with weather and air pollution data at the zip code level at a daily timescale. We join this data to our injury data, which records the number of workers injured by zip code and date from 2000 to 2021.

TABLE 3.1. Summary Statistics

Statistic	Mean	Median	St. Dev.	Min	Max	N
Injuries	0.073	0	0.320	0	28	1,121,955
Downwind	1.651	0	3.364	0	94	1,121,955
Downwind (>0)	3.397	2	4.166	1	94	545,125
$PM_{2.5}$ (μg/m^3)	9.568	7.612	7.554	0.0001	173.657	836,337
Temperature (F)	71.895	70.771	13.431	25.038	111.855	1,121,955
Precipitation (Inch)	0.047	0.000	0.177	0.000	6.904	1,121,955
Wind Speed (m/s)	3.247	3.010	1.474	1.000	15.908	1,121,955

Notes: Table 3.1 displays the average values of key variables across the sample period. 'Downwind' indicates the number of fires upwind that affect the downwind zip codes as illustrated in Figure 3.4. 'Downwind (> 0)' indicates the number of fires conditional on a zip code is affected by any number of upwind fires.

3.3.5. Summary Statistics. Table 3.1 shows the summary statistics of the key variables. On average, we observe 0.073 injuries in a zip code on a day during the sample period. A limitation of using workers'-compensation data is the potential for underreporting the true number of injuries. This underreporting can come from workers' fears of repercussions from their employers or from the belief that an injury may not be severe enough to warrant reporting (Haiduven et al., 1999; Kyung et al., 2023; Pompeii et al., 2016; Rosenman et al., 2000). This issue may be particularly salient for undocumented workers, who might opt not to seek medical care due to concerns about retaliation from their employers. Moreover, claims can be denied if administrators determine that there is insufficient evidence linking the injuries to work-related activities (CDIR, 2022). A fear of rejection could discourage workers from reporting chronic illnesses, such as respiratory and circulatory conditions, that are challenging to attribute to a specific work-related incident (Biddle, 2001; InvictusLaw, 2022).

Instances of respiratory and cardiovascular claims are rare in our data, with only 2,113 cases reported between 2000 and 2021, making up about 0.57% of the total sample. The number of respiratory cases declines to 771 for 21 years in our final dataset when we restrict our sample to injuries that occurred within 30 km of burning sites. This indicates there are only 35 respiratory illness claims in a year on average. To put this into perspective, emergency room (ER) visits in California attributed to respiratory diseases during the same timeframe accounted for 11% of all ER visits (Heft-Neal et al., 2023c). Conversely, traumatic injuries such as strains, tears, contusions, and lacerations dominate our dataset, constituting a significant 78.54% of all reported injuries. As a result, we focus on the broader effects of agricultural burning on all injury types.

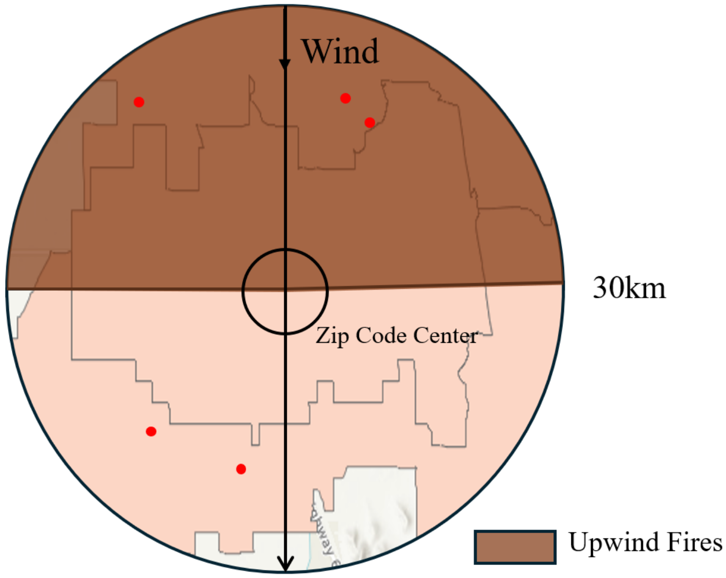
All observations are either downwind or upwind of agricultural burning fields. On average, when a zip code is on downwind of burning sites (Downwind > 0), approximately 3.4 agricultural fires occur within the 30 km boundaries during a given day.

3.4. Research Design

Distinguishing the health consequences of pollution from agricultural fires from the effects of other socioeconomic variables, such as economic activities linked to agricultural burning, is challenging (Pullabhotla et al., 2023). Accurately measuring health impacts requires separating the adverse effects of pollution from any potential health or economic benefits associated with the burning.

Prior literature relies on wind direction as an exogenous source of variation to identify the effects of air pollution on various outcomes such as health and crime (Deryugina et al., 2019; Herrnstadt et al., 2021; Pullabhotla et al., 2023; Rangel and Vogl, 2019). Our empirical strategy leverages exogenous wind direction and fire location data at a daily level to address identification challenges stemming from seasonal and economic factors related to agricultural burning. We study injuries among workers exposed to varying levels of agricultural burning downwind of fires, driven by shifts in plausibly random wind direction. We only use the $PM_{2.5}$ levels and injury counts from zip codes located within a 30 km radius of agricultural burning sites, which are likely to be affected by the burning.

FIGURE 3.4. Schematic showing Definition of Downwind



Notes: Each dot represents an agricultural fire. The darker semicircle area includes upwind fires that are counted in the 'Downwind' variable. Note that 'Downwind' indicates the number of upwind fires affecting the downwind zip codes. For example, in this illustrative figure, there are three fires occurring in the upwind fire regions. Consequently, 'Downwind' in equation 3.1 becomes three for the zip code on that day.

We begin with a first stage and show that areas located downwind of agricultural fires have higher levels of $PM_{2.5}$ relative to areas located upwind using the following model:

$$\text{PM}_{z,d} = \beta_1 \,\text{Downwind}_{\text{z,d}} + \mathbf{W}_{z,d}\Pi + \tau_{yz} + \mu_d + \epsilon_{z,d} \tag{3.1}$$

where $\text{PM}_{z,d}$ is the $PM_{2.5}$ level on day d, at the zip code z. $\text{Downwind}_{z,d}$ counts the number of upwind agricultural fires that a downwind zip code experiences on a given day. We define upwind fires as those located within 90 degrees from the center of a zip code relative to the prevailing daily wind direction, as illustrated in Figure 3.4. To address potential confounding factors, we incorporate a host of fixed effects in our analysis. Specifically, we include year-by-zip-code (τ_{yz}) fixed effects to control for any yearly shocks by zip code such as the change in the composition of crop types over the years. Additionally, day-of-the-year (μ_d) fixed effects are used to remove any differences between day-of-the-year related to agricultural burning schedules such as workdays as well as to account for seasonality in both agricultural burnings and worker injuries. Standard errors are two-way clustered by zip code and date to account for correlated factors within zip code and date. [1]

We control for local weather conditions, $\mathbf{W}_{z,d}$, daily maximum temperature, precipitation, and wind speed. Temperature variables are binned into 15 categories in zip code z on day d. Categories range from below 40°F, increasing in 5°F increments, up to over 105°F. Similarly, precipitation is divided into four categories, representing daily total precipitation in inches in zip code z on day d, with increments increasing by half an inch from 0 to over 1. The wind speed is categorized into four bins: 0 to 5 m/s, greater than 5 to 10 m/s, greater than 10 to 15 m/s, and above 15 m/s.

Pollution levels may be affected not only by the number of burnings but also by the tonnage burned. We further explore whether the increase in average tons burned leads to higher $PM_{2.5}$ levels. Note that although we gather administrative data from seven air districts, only three – San Joaquin, Monterey, and Ventura Air Districts – provide information on burned tonnage.

To explore whether the effects vary as the tons burned increases, we estimate the following equation:

$$\begin{aligned}\mathrm{PM}_{z,d} &= \beta_1 \mathrm{Downwind}_{z,d} \times \mathrm{Tons}(0-5)_{z,d} + \beta_2 \mathrm{Downwind}_{z,d} \times \mathrm{Tons}(>5)_{z,d} \\ &\quad + \mathbf{W}_{z,d}\Pi + \tau_{yz} + \mu_d + \epsilon_{z,d}\end{aligned} \tag{3.2}$$

where $\mathrm{Tons}(0-5)_{z,d}$ and $\mathrm{Tons}(>5)_{z,d}$ are indicator variables. $\mathrm{Tons}(0-5)_{z,d}$ takes the value of 1 when the average tons burned for all agricultural burnings affecting the downwind zip code are greater than 0 but less than or equal to 5. $\mathrm{Tons}(>5)_{z,d}$ is assigned a value of 1 if the average tons burned exceed 5, and 0 otherwise. We divide the groups based on 5 tons, which represents the median of the sample.

Next, we estimate the effects of agricultural burning on worker injuries:

$$\mathrm{Injury}_{z,d} = \beta_1 \, \mathrm{Downwind}_{z,d} + \mathbf{W}_{z,d}\Pi + \tau_{yz} + \mu_d + \epsilon_{z,d} \tag{3.3}$$

$$\begin{aligned}\mathrm{Injury}_{z,d} &= \beta_1 \mathrm{Downwind}_{z,d} \times \mathrm{Tons}(0-5)_{z,d} + \beta_2 \mathrm{Downwind}_{z,d} \times \mathrm{Tons}(>5)_{z,d} \\ &\quad + \mathbf{W}_{z,d}\Pi + \tau_{yz} + \mu_d + \epsilon_{z,d}\end{aligned} \tag{3.4}$$

where the $\mathrm{Injury}_{z,d}$ indicates the number of agricultural worker injuries that occurred in a given zip code, z, on a given day, d. For robustness, we also present the effects of agricultural burning within a 10 km and 50 km radius of a fire in Table S3.2.

[1] Table S3.3 shows that results are robust to alternative choices of clustering levels.

The effects of agricultural burning over consecutive days may be larger than a single day of burning. To explore this possibility, we use the following model:

$$\text{Average Injury}_{z,d} = \alpha_1 \text{Downwind Days}_{z,d} + \mathbf{W}_{z,d}\Pi + \tau_{yz} + \mu_d + \epsilon_{z,d} \tag{3.5}$$

where Downwind $\text{Days}_{z,d}$ indicates the consecutive number of days that a zip code experienced agricultural burning. Average $\text{Injury}_{z,d}$ indicates the average injuries over days that occurred during those consecutive days. For example, if a zip code experienced agricultural fires for 3 consecutive days, 'Downwind Days' is recorded as 3, and the 'Average Injury' represents the average number of injuries that occurred over this three-day period. Figure S3.1 shows the distribution of the number of zip codes and days in our sample across multiple days of burning. Approximately 68% of the burnings occur over multiple days, while about 32% are single-day events. The median number of consecutive burning days is approximately 2.

In all our samples, following Rangel and Vogl (2019), we exclude zip codes located within 5 km of any fires to ensure that injuries are not directly influenced by the fire itself but rather by the smoke from agricultural burning. Results are robust to the inclusion of injuries within 5 km. We further restrict the sample when wind speed is above 1 m/s corresponding to a gentle breeze to ensure the effectiveness of the identification strategy that relies on the wind that disperses smoke from agricultural burning. Even if a zip code is located downwind, if the wind speed is too slow to effectively disperse the smoke, there may be no discernible variation in smoke levels between upwind and downwind conditions. Results remain robust even when wind speeds of 1 m/s or less are included.

3.5. Results

We begin with presenting results for the first stage: Do agricultural burnings increase $PM_{2.5}$ levels? We then turn to the effects of smoke from burning on workers' injuries: Do injuries increase downwind of burning sites? Further, we explore the possibility of larger effects from multiple-day burnings: Do consecutive days of burning have larger effects on workers' injuries than single-day burning? We also investigate heterogeneous responses by age. Finally, we conduct several robustness checks to demonstrate the reliability of our findings.

3.5.1. Agricultural Burning and $PM_{2.5}$.

TABLE 3.2. Agricultural Burning and $PM_{2.5}$

	All Fires			Fires over 20 Tons	
	(1)	(2)	(3)	(4)	(5)
Downwind	0.0977***	0.0972***		0.2166***	0.0888***
	(0.0154)	(0.0158)		(0.0362)	(0.0338)
Downwind x Tons (0-5)			0.0832***		
			(0.0152)		
Downwind x Tons (> 5)			0.1487***		
			(0.0248)		
Dependent Variable Mean	9.568	9.568	9.568	11.27	11.27
Control Variable Mean	8.906	8.906	8.906	10.20	10.20
Observations	836,337	836,337	619,704	117,920	117,920
R^2	0.29398	0.32190	0.29732	0.34212	0.44665
Fires > 20 Tons				✓	✓
Weather Controls	✓	✓	✓	✓	✓
Year fixed effects	✓				
Day fixed effects	✓	✓	✓	✓	✓
Zip Code fixed effects	✓				
Year x Zip Code fixed effects		✓	✓	✓	✓
County x Month fixed effects					✓

Notes: Table 3.2 shows the results following equation 3.1 for columns (1),(2), (4), and (5). Column (3) presents the result for equation 3.2.
* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

We begin by estimating the $PM_{2.5}$ levels downwind of the agricultural burning sites within 30km of the zip code following equation 3.1 and 3.2. Table 3.2 reports results. When zip codes are downwind of burning sites, $PM_{2.5}$ levels are higher across specifications. In column (2), the result of our preferred specification, where day-of-the-year and year-by-zip-code fixed effects are used, shows that the increase in one additional fire affecting a zip code results in a $PM_{2.5}$ increase of about 0.097 μg/m^3. In column (1), when we use zip code and year-fixed effects instead of year-by-zip-code fixed effects, the estimated effect is slightly larger than our preferred estimate.

Column (3) reports the results of equation 3.2, which explores the varied effects of tons burned on $PM_{2.5}$ concentration. Note that the sample size to estimate the results in columns (3)–(5) is smaller than that used in columns (1) and (2) because only certain air districts record the amount of burned tons. As expected, the effects of burnings increase with the size of the fire. When we subset agricultural burnings burned over 20 tons, one more agricultural burning increases $PM_{2.5}$ by about 0.22 μg/m^3 as presented in column (4). This indicates that $PM_{2.5}$ increases by about 0.75 μg/m^3 on downwind days considering that, on average, 3.4

agricultural fires affect the downwind zip code for a given day. This translates to a 6.64 % increase in $PM_{2.5}$ compared to days without agricultural burnings.

Our estimates are in line with the earlier works. We can compare these estimates with earlier work on the effects of global biomass burning on $PM_{2.5}$. Pullabhotla et al. (2023) find that the 1 km^2 increase in the burned area leads to 0.49 $\mu g/m^3$ increase in $PM_{2.5}$ concentration. Considering that the average burned area in our sample for one burning is 0.02 km^2, 1 km^2 burning corresponds to about 4.86 $\mu g/m^3$ increase in $PM_{2.5}$ concentration on downwind area, which is larger than Pullabhotla et al. (2023)'s finding. Next, we compare our estimates with the results of Ferguson (2023), which studies the effects of agricultural burning on $PM_{2.5}$ in Sacramento, California. Ferguson (2023) find that 1 km^2 increase in burned area increases $PM_{2.5}$ levels by 6 $\mu g/m^3$ which is larger than our finding. Zivin et al. (2020) additionally find that one additional fire increases $PM_{2.5}$ levels by 0.262 $\mu g/m^3$ in China, which is comparable with the finding in column (4) where the average tons burned is more than 20. In summary, our estimates fall within the range of findings reported in previous studies in various contexts.

3.5.2. Agricultural Burning and Injuries. Next, we examine the impacts of agricultural burning on worker injuries. In our preferred specification in column (2), we find that when wind blows in the downwind direction of burning sites, there is an increase of 0.56 injuries per thousand agricultural workers. This corresponds to roughly a 0.76 percent rise in injuries within the affected area. On average, conditional on being located downwind of burning, downwind zip codes in our sample experience 3.4 daily agricultural fires. This implies that on days with agricultural burnings, there is a 2.6 percent increase in injuries within the downwind zip code. Column (1) uses year and zip-code fixed effects rather than year-by-zip-code fixed effects, thereby eliminating year-specific and zip-code-specific shocks instead of capturing common shocks within each zip code and year. The estimated effect is slightly larger compared to our preferred specification. Moreover, as shown in column (3), the impact of smoke from fires downwind is increasing in the average amount of burned tons. Specifically, when the average number of tons burned exceeds 5, approximately 0.92 additional injuries per thousand workers occur compared to days without burning.

We now compare our estimates to those of related studies. He et al. (2020) find that an increase in the number of fires affecting downwind areas leads to a 5.02 percent rise in monthly mortality in China which is larger than our estimate. The relatively smaller effects observed in our study can be attributed to several factors. One possible explanation is that He et al. (2020) identify straw burning using remote sensing data

TABLE 3.3. Agricultural Burning and Worker's Injury

	All Fires			Fires over 20 Tons	
	(1)	(2)	(3)	(4)	(5)
Downwind	0.6090***	0.5579***		0.7848*	1.022**
	(0.1733)	(0.1840)		(0.3992)	(0.4061)
Downwind x Tons (0-5)			0.3214		
			(0.3255)		
Downwind x Tons (> 5)			0.9209***		
			(0.2357)		
Dependent Variable Mean	73.12	73.12	73.12	106.2	106.2
Control Variable Mean	61.57	61.57	61.57	96.77	96.77
Observations	1,121,955	1,121,955	799,031	164,595	164,595
R^2	0.12085	0.14600	0.14527	0.17172	0.17392
Fires > 20 Tons				✓	✓
Weather Controls	✓	✓	✓	✓	✓
Year fixed effects	✓				
Month fixed effects	✓				
Day fixed effects	✓	✓	✓	✓	✓
Zip Code fixed effects	✓				
Year x Zip Code fixed effects		✓	✓	✓	✓
County x Month fixed effects					✓

Notes: Table 3.3 shows the results following equation 3.3 for columns (1),(2), (4), and (5). Column (3) presents the result for equation 3.4. The dependent variable, injury, is multiplied by 1,000.
* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

from satellites. As outlined in the data section, satellite data primarily capture very large agricultural fires that are visible from space. Therefore, the larger effects observed in He et al. (2020)'s study may result from their focus on detecting the effects of larger fires on mortality. Additionally, differences in adaptation levels could contribute to the differences in effects observed. He et al. (2020) suggest that their estimates are unlikely to be influenced by avoidance behavior in China. In contrast, farmworkers in California do engage in avoidance behavior along several dimensions in response to wildfire smoke as documented in Beatty and Lee (2024b), which is likely to reduce the relationship between smoke exposure and injury. Note that our estimates are an equilibrium result that reflects this adaptation behavior, not the dose-response relationship between burning and injuries, which does not consider this relationship.

Next, we compare our effect sizes to the effect of wildfire smoke on morbidity in California. Heft-Neal et al. (2023c) find that wildfires lead to a 1.1 percent increase in total emergency department visits for individuals in California during the following week. This effect size is comparable to the results for one additional agricultural fire burning when tons burned exceed 5. However, when we compare Heft-Neal et al. (2023c)'s estimate with the effect of the daily average number of agricultural fires on injuries (2.6 percent), our estimate is larger. Our larger effect in our study's setting seems reasonable given the vulnerability and proximity of agricultural workers to smoke. Many work outdoors near burn sites and engage in physically demanding tasks, which significantly increases both their exposure and vulnerability to air pollution compared to the general public.

TABLE 3.4. Consecutive Agricultural Burning

	All Fires			Fires over 20 Tons	
	(1)	(2)	(3)	(4)	(5)
Downwind Days	0.3344***	0.3291***		0.5986***	0.5810***
	(0.0767)	(0.0857)		(0.1701)	(0.1687)
Downwind Days x Tons (0-5)			0.2696***		
			(0.1013)		
Downwind Days x Tons (> 5)			0.4715***		
			(0.0978)		
Dependent Variable Mean	64.99	64.99	64.99	0.2692	0.2692
Control Variable Mean	61.56	61.56	61.56	0.0967	0.0967
Observations	755,696	755,696	502,461	95,734	95,734
R^2	0.13714	0.16529	0.16693	0.21165	0.21454
Fires > 20 Tons				✓	✓
Weather Controls	✓	✓	✓	✓	✓
Year fixed effects	✓				
Zip Code fixed effects	✓				
Day fixed effects	✓	✓	✓	✓	✓
Year x Zip Code fixed effects		✓	✓	✓	✓
County x Month fixed effects					✓

Notes: Table 3.4 shows the results using equation 3.5. The dependent variable, Average Injury, is multiplied by 1,000.

3.5.3. Consecutive Event. The effects of agricultural burning over multiple days may be significantly larger than those of a single day of burning. We investigate whether multiple days of exposure to agricultural burning events have a greater impact on worker injuries than one-day burning. Prior work has largely focused on the contemporaneous effect of air pollution. It often elides prolonged exposure periods, which are increasingly common. Multiple-day exposure may have different health impacts compared to a single day of exposure. Zhang et al. (2018) find that as the duration of students' exposure to air pollution increases—from 1 day, 7 days, 30 days, to several years—their test scores decrease nonlinearly. Similarly, cumulative damage from multiple days of smoke exposure from agricultural burning may result in more injuries compared to single-day exposure.

Table 3.4 reports results from equation 3.5, which estimates the relationship between agricultural burning over consecutive days and the average injuries that occurred during these multiple burning days. We find that for each additional day impacted by smoke from agricultural burning, there is a 0.51% rise in the average number of injuries observed. Effects are larger as burned tons increase, as demonstrated in columns (3) and (4). In our sample, conditional on being affected by burning, the median zip codes in our sample experienced approximately two consecutive days of agricultural burning. Notably, the top 10% of instances involve experiencing ten consecutive days of such burnings. This finding suggests that prolonged exposure to multi-day burning events exacerbates the detrimental effects on agricultural workers' injuries, emphasizing the potential necessity for regulations aimed at limiting consecutive burning events.

3.5.4. Age. We now investigate whether the impact of burning differs across worker ages. Agriculture faces persistent labor shortages (Charlton and Taylor, 2016; Hertz and Zahniser, 2013). One significant issue exacerbating the labor shortage problem is the aging workforce in agriculture. From 1979 to 2019, the median age of a California worker rose by seven years, from thirty-three to forty years old (UC Merced Community and Labor Center, 2023). As vulnerability to smoke and air pollution increases with age (Deryugina et al., 2019; Schlenker and Walker, 2016), older workers may be more susceptible to injury from smoke exposure during agricultural fires. Their exit from work due to serious injury or voluntary withdrawal to avoid work hazards could further aggravate the labor shortage issue. To explore this, we categorize the sample into two groups: workers aged below 45 and workers aged greater or equal to 45.

We find that smoke from agricultural burning has a larger impact on older workers relative to younger ones. Specifically, for workers aged 45 and above, the effect of one additional agricultural burning results in approximately a 0.98 percent increase in downwind injuries. Conversely, the effect of burning on workers younger than 45 is statistically insignificant, with a smaller effect size of about 0.36 percent increase in injuries.

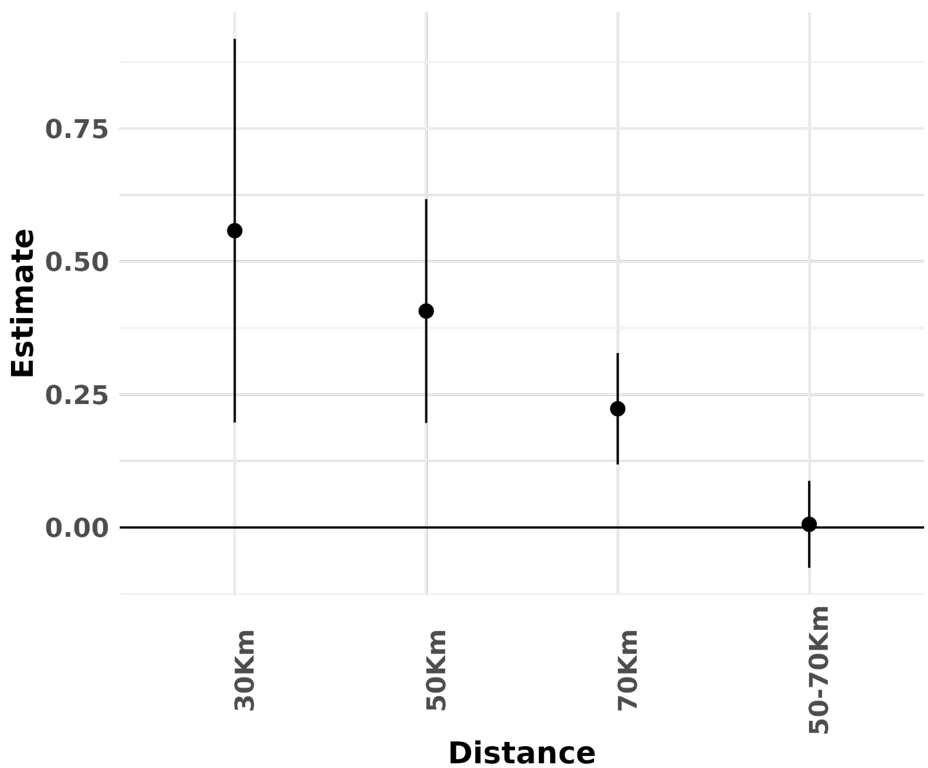
3.5.5. Robustness Checks.

TABLE 3.5. Age

	Below 45 (1)	Above 45 (2)
Downwind	0.1259	0.2056***
	(0.1178)	(0.0668)
Dependent Variable Mean	34.91	20.97
Control Variable Mean	29.89	17.45
Effect relative to mean, percent	0.3608	0.9801
Observations	796,737	796,737
R^2	0.09223	0.05656
Weather Controls	✓	✓
Year x Zip Code fixed effects	✓	✓
Day fixed effects	✓	✓

Notes: Table 3.5 shows the results following equation 3.3 categorized by age groups. The age categories are defined as follows: 'Below 45' includes individuals under the age of 45 and 'Above 45' encompasses those aged greater or equal to 45. The dependent variable, injury, is multiplied by 1,000.

FIGURE 3.5. Distance



Notes: Figure 3.5 displays the results based on equation 3.3. The estimates from left to right are derived from samples located within 30 km, 50 km, and 70 km of the agricultural burning, respectively. The right-most estimate is from a sample located 50-70 km from the agricultural burnings. The dependent variable, injury, is scaled by multiplying by 1,000.

In this section, we assess the robustness of our findings. In our main sample, we specifically examine the impact of agricultural fires occurring within a 30km radius from workers. We generate additional samples and replicate our primary analysis to assess how expanding or reducing this distance influences injury outcomes. Results are detailed in Figure 3.5 and Table S3.2.

Results are consistent with increased effects as the distance to the burn sites decreases. When we expand our sample to zip codes within a 50 km radius of burning sites, agricultural burning causes injuries to rise by about 0.41 workers per thousand, which represents a 0.73 percent increase. The magnitude is slightly smaller than the estimate from our main sample of zip codes within a 30 km radius. However, as we extend further to a 70 km radius, the effect decreases to 0.22 workers per thousand, which is about a 0.52 percent increase. Furthermore, when we specifically look at zip codes between 50 and 70 km from the fire, the impact is not statistically different from zero, with only about 0.03 percent increase in injuries for each additional fire.

3.6. Discussion & Conclusion

While agricultural burning has long been common in the U.S., the effects of such burning in the U.S. remain understudied relative to developing countries. Further, prior studies often rely on remote sensing burning due to a lack of burning permit regulations in the study region. Leveraging daily permit data with precise location information, we find that $PM_{2.5}$ levels are higher in the downwind region of the agricultural burning sites. We also find that being exposed to smoke from agricultural burning is linked to a rise in injuries among agricultural workers. The impact on injuries becomes more substantial when agricultural burnings occur on consecutive days.

Although the first stage analysis is not the main focus of this paper, one of the limitations of our study comes from potential measurement errors in $PM_{2.5}$ data, given our focus on rural areas with limited monitoring stations. Despite our efforts to mitigate these errors by using NASA's data produced with rigorous statistical methods, the scarcity of monitoring stations may still introduce measurement errors. Exploring the impact of agricultural burning on $PM_{2.5}$ with improved air pollution data could be a fruitful research area for advancing our understanding of the impact of agricultural burning on air quality in rural settings.

Our findings have important implications for existing agricultural burning regulations and outdoor-worker protection policies. Our study centers on California with rigorous regulations on agricultural burning. In contrast, many states, such as Texas, do not regulate agricultural burning and do not require permits for it (Treadwell and Lashmet, 2021). This absence of policy suggests that health costs stemming from agricultural burning nationwide may be significant, highlighting the opportunity for comprehensive policies safeguarding workers from the air pollution associated with such practices.

The results of this study also have implications for California's regulation. This study indicates the necessity of expanding the current 5141.1 Protection from Wildfire Smoke policy, originally designed for wildfire smoke, to also include protection from agricultural burning smoke. While the existing policy may protect outdoor workers from wildfire smoke, we have identified that smoke from agricultural burning is also a substantial threat to the health of agricultural workers. Therefore, our findings suggest the need for broader protection regulations that encompass smoke generated by agricultural burning.

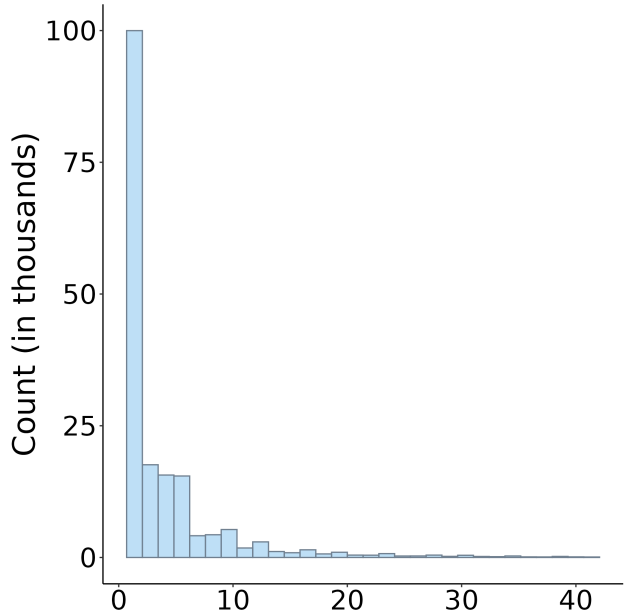
3.7. Appendix

TABLE S3.1. Available Years for Each District

	District	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
1	Feather River				X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
2	Monterey Bay											X		X	X	X	X		X		X	X	X
3	Nothern Sonoma County										X	X	X	X	X	X	X	X	X	X	X	X	X
4	Sacramento Metro	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
5	San Joaquin Valley	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
6	Ventura																		X	X	X	X	X
7	Yolo-Solano																X	X	X	X	X	X	X

Notes: For Monterey Bay, years not available between 2010 and 2020 are the years when there is no location information provided which means we are not able to identify where the agricultural burning took place.

FIGURE S3.1. The Number of Multiple Day Burnings



Notes: Figure S3.1 shows the distribution of the number of zip codes and days that experienced consecutive days of burning in our sample. The top 1% of days with the highest number of consecutive burnings are excluded.

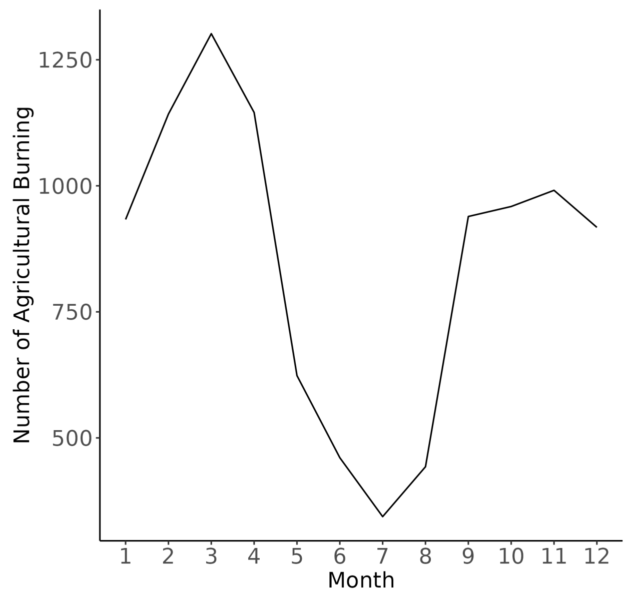
TABLE S3.2. Distance

	30 km (1)	50 km (2)	70 km (3)	50-70km (4)
Downwind	0.5579***	0.4068***	0.2231***	0.0059
	(0.1840)	(0.1073)	(0.0534)	(0.0417)
Dependent Variable Mean	55.68	73.12	42.86	21.05
Control Variable Mean	40.62	61.57	27.73	20.67
Effect relative to mean, percent	0.7630	0.7307	0.5206	0.0280
Observations	1,121,969	1,844,629	2,763,631	1,388,761
R^2	0.14600	0.14073	0.14241	0.12400
Weather Controls	✓	✓	✓	✓
Year x Zip Code fixed effects	✓	✓	✓	✓
Day fixed effects	✓	✓	✓	✓

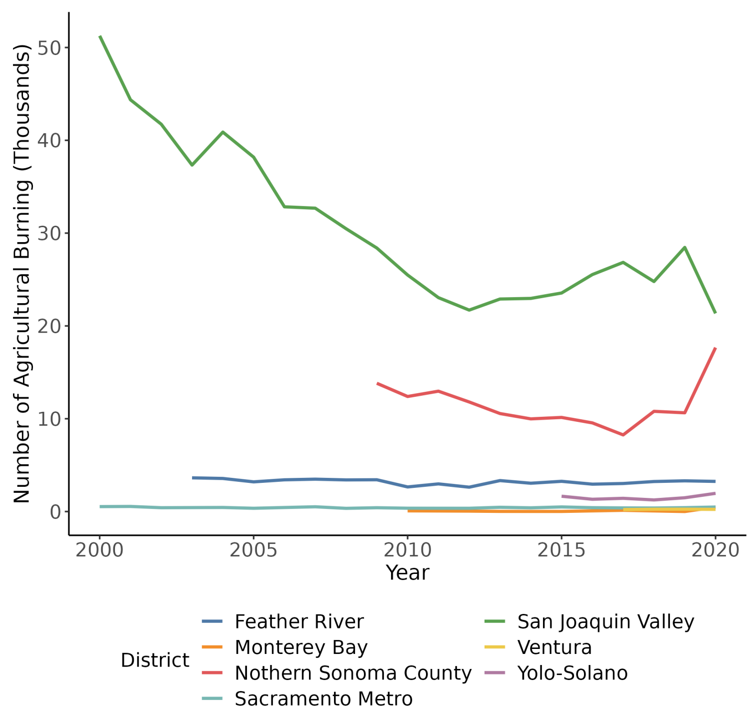
Notes: Table S3.2 displays the results based on equation 3.3. In columns (1)–(3), the estimates are derived from a sample located within 30 km, 50km, and 70km of the agricultural burning, respectively. The estimate in column (4) presents the result from a sample located within 50-70km of the agricultural burnings. The dependent variable, injury, is multiplied by 1,000.

FIGURE S3.2. Permit by Year and Month

(a) Permits by Month



(b) Permits by Year



Notes: Panel (a) shows the average number of permits by air district by month in California and Panel (b) plots the total number of permits by year for each air district.

TABLE S3.3. Cluster

	(1)	(2)	(3)
Downwind	0.5579**	0.5579**	0.5579**
	(0.2370)	(0.2418)	(0.2112)
Standard-Errors	County & Date	Zip Code & Week	Zip Code & Year
Observations	1,121,955	1,121,955	1,121,955
R^2	0.14600	0.14600	0.14600
Weather Controls	✓	✓	✓
Year x Zip Code fixed effects	✓	✓	✓
Day fixed effects	✓	✓	✓

Notes: Table S3.3 shows the results following equation 3.3 estimated with different set of clusters. The dependent variable, injury, is multiplied by 1,000.

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