Stochastic Caregiving Shocks and Mothers' Labor Market Outcomes: Evidence from Wildfire Smoke

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Abstract

Formal childcare and public schooling are widely understood to be central to mothers' labor market attachment. Yet a large literature finds that even substantial expansions in access to formal care often produce modest or null effects on maternal employment. This paper studies the role of stochastic caregiving demand shocks that cause childcare constraints to bind intermittently even when formal care is available. Using plausibly exogenous variation in wildfire smoke exposure—which we show increases the likelihood of school closures—and comparing mothers of children at different ages who vary in their reliance on schools for childcare, we demonstrate that these shocks impose substantial contemporaneous costs on employed mothers and that their accumulation reduces employment among affected mothers by 1 percent. We further show that workplace cultures that tolerate unpredictability can mitigate the negative impact of caregiving shocks.

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1 Introduction

Over the past several decades, governments in many countries have expanded access to formal childcare and schooling, substantially reducing routine caregiving demands on parents—particularly on mothers, who continue to bear a disproportionate share of childcare responsibilities (Kleven et al., 2024). However, a large literature documents that these policies have not fully restored mothers' labor market outcomes to pre-childbirth levels, resulting a significant loss of human capital and labor productivity.[1] Existing explanations emphasize preference-based channels, such as gendered social norms (Kleven et al., 2019; Andresen and Nix, 2022; Kleven et al., 2024) as well as constraint-based channels arising from rigid work arrangements (Goldin, 2014; Cortés and Pan, 2019; Gibbs et al., 2025). These papers implicitly treat caregiving demands as stable and predictable, abstracting away from the stochastic nature of them. However, even when formal care is nominally available, unexpected caregiving shocks such as child illness or school closures can cause constraints to bind intermittently, creating a "reliability gap" for employed mothers.

As detailed in Section 2, theory suggests that these caregiving shocks impose immediate utility costs on employed mothers, and when they accumulate, can reduce the value of employment relative to non-employment and trigger labor force exit. Despite the theoretical importance of this reliability gap, limited causal evidence exists on these effects, likely because directly observing such disruptions is difficult. We address this challenge by leveraging a plausibly exogenous, environmentally driven source of caregiving shocks: wildfire smoke–induced school closures. By exploiting variation in smoke exposure that disrupts school operations, and by comparing mothers of children at different ages who differ in their reliance on schools for childcare, we estimate the labor market cost of caregiving shocks on mothers.

Recently, wildfire smoke has accounted for up to 25% of total $PM_{2.5}$ (particulate matter with aerodynamic diameter $< 2.5, \mu$m) nationwide, making it one of the most significant sources of ambient air pollution (Burke et al., 2021). Due to its detrimental impact on children's health, wildfire smoke has become a leading cause of school closures (Abatzoglou and Williams, 2016; Miller and Hui, 2022). For empirical exercise, we combine data on labor market outcomes, time use, and school closure with county-by-day wildfire smoke exposure data from Childs et al. (2022) over the 2006–19 period.

[1] For instance, see Gelbach (2002); Cascio (2009); Fitzpatrick (2010, 2012); Havnes and Mogstad (2011); Kleven et al. (2024); Duchini and Van Effenterre (2024).

To estimate the effect of wildfire smoke on school closures, we exploit plausibly exogenous variation in smoke exposure, driven by the unpredictability of wildfire outbreaks and long-range wind transport (Wen and Burke, 2022; Borgschulte et al., 2024). To examine how smoke-driven caregiving demand shocks affect maternal labor outcomes, we implement a triple-difference design to isolate the childcare channel from the direct health effects of smoke exposure, which are known to adversely affect labor outcomes (Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015; Borgschulte et al., 2024). Specifically, we compare smoke's impact on labor outcomes for "treated" mothers—those whose youngest child is aged 5–12 (elementary school age)—to "control" mothers whose youngest child is aged 0–4 or 13–17. This comparison is motivated by baseline time use patterns, which show that mothers of elementary school-aged children experience the largest drop in weekday childcare responsibilities relative to weekends, compared to mothers with younger children (aged 0-4), who do not benefit from public schooling yet, and those with older children (aged 13-17), who require much less care in the first place.

Our empirical exercises produce three findings. First, wildfire smoke seriously disrupts school operations. Using administrative school closure data from California, we show that a smoke day—defined throughout the paper as a day with wildfire-driven $PM_{2.5}$ exceeding $3\mu g/m^3$—increases the probability of having any school closure at the county level by 250%.[2] In addition, the closure probability increases monotonically with the intensity of the smoke, reaching 750% for days when the wildfire-driven $PM_{2.5}$ exceeds $7\mu g/m^3$. Importantly, while these results indicate that school closures are a key source of caregiving demand shocks, they are not likely to be the only one. Even when schools remain in operation, smoke exposure can independently create caregiving demand shocks, for instance by increasing child illness (Aguilera et al., 2021; Syed and Basu, 2025).

Having established the "first-stage" relationship between wildfire smoke and caregiving demand shocks, we turn to its effects on maternal time use and contemporaneous labor outcomes. Using the American Time Use Survey (ATUS), we find that treated mothers increase time spent on childcare by 53 minutes (or 14.7%) during wildfire smoke events—but only on weekdays—suggesting that changes in time usage reflect disruptions to formal childcare available on weekdays. Consistent with this, we show that one additional weekday of smoke exposure during the Current Population Survey

[2]Wildfire driven $PM_{2.5}$ exceeding $3\mu g/m^3$ corresponds to the average level of increase in total $PM_{2.5}$ observed on a wildfire smoke day (Burke et al., 2023).

(CPS) survey week reduces the likelihood of being at work by 0.15 percentage points (3.7%) and weekly working hours by six minutes (0.3%) among treated mothers, conditional on employment. Even though mothers can adjust along multiple margins (e.g., paying for emergency care or relying on social networks to remain at work that day), smoke-driven caregiving shocks still reduce labor supply for an average mother, indicating that these shocks are large enough that some adjustment occurs through reductions in labor supply.

Lastly, we examine whether these short-term disruptions translate into longer-term consequences. Using the CPS data, we estimate the effect of cumulative wildfire smoke over the prior 12 months on maternal employment. We find that each additional weekday smoke exposure reduces the likelihood of employment by 0.07 percentage points (or 0.11%). At the sample average of 8.6 smoke days per year, this implies a 1% decline in employment probability. While some studies find sizable employment responses to childcare expansion, many, including in the US setting, document small or null effects.[3] Given this, a 1% reduction suggests that unexpected caregiving shocks meaningfully erode the maternal employment gains of formal childcare.

These longer-run effects are concentrated in full-time employment and are driven by labor force exit rather than unemployment, indicating that wildfire smoke may lead some mothers to leave work altogether rather than temporarily step back. Moreover, the frequency of episodes, rather than each episode's duration, appears to be the key driver, suggesting that even minor but repeated disruptions can accumulate into sizable and persistent labor market consequences. We also find evidence of non-linear effects: the impact on job exit increases sharply once exposure exceeds 14 smoke days, suggesting that sufficiently frequent shocks trigger discrete extensive-margin responses.

We further show that the job exit effect is not mitigated by factors that lower the resource costs of caregiving shocks. Neither access to informal backup care, which allows mothers to provide care at lower cost than market alternatives, nor higher worker substitutability, which reduces earnings penalty from reduced working hours Goldin (2014), attenuates the effect. This is consistent with Adams et al. (2025), who document persistent gender gaps for mothers in online labor markets, where substitutability is high by construction, due to work interruptions related to childcare. In-

[3]Baker et al. (2008) and Andresen and Havnes (2019) find a large employment effect in Canada and Norway. In contrast, Fitzpatrick (2010, 2012), Kleven et al. (2024), Havnes and Mogstad (2011), Goux and Maurin (2010), and Nollenberger and Rodríguez-Planas (2015) find small or null effects for an average mother in the US, Australia, Norway, France, and Spain.

stead, resiliency to caregiving shock seems to critically depend on workplace culture that tolerate unpredictability: we find that the job exit effect is concentrated among mothers employed in male-dominant industries.

Related literature. This paper contributes to four strands of the literature. First, we contribute to the literature on the motherhood penalty by investigating an understudied mechanism: the reliability gap. While a large literature attributes motherhood penalty to preference-based channels (Blau et al., 2011; Angelov et al., 2016; Kleven et al., 2019; Andresen and Nix, 2022; Kleven et al., 2024) or rigid job structure (Bertrand et al., 2010; Goldin, 2014; Goldin and Katz, 2016; Cortés and Pan, 2019), our findings highlight how the stochastic nature of caregiving creates a distinct hurdle for employed mothers. In that sense, we build on a nascent branch of the motherhood penalty literature that investigates the labor market impact of work interruptions (Cubas et al., 2021; Frech and Maideu-Morera, 2024; Adams et al., 2025; Anstreicher and Jack, 2025).

Within this strand, our paper is most closely related to Adams et al. (2025), who study gender gaps in earnings on an online labor platform. They document that gender earnings gaps persist even in this flexible work environment because female workers, particularly mothers, exhibit lower productivity, which they attribute to routine work interruptions due to caregiving. Our analysis differs along three key dimensions. First, we study a different type of disruption: externally imposed caregiving shocks, such as smoke-driven school closures, that are larger but rarer and occur unpredictably. Second, while Adams et al. (2025) focus on contemporaneous productivity effects, we demonstrate that repeated caregiving shocks lead to permanent labor force exit. Third, we use nationally representative data rather than a single platform.

Second, we contribute to the literature on childcare infrastructure and maternal labor supply. Prior research has primarily evaluated the impact of childcare availability—the "quantity" of affordable slots—on labor outcomes. This includes studies on public school eligibility (Gelbach, 2002; Cascio, 2009; Fitzpatrick, 2012), the expansion of subsidized care or the temporal coverage of the school (Baker et al., 2008; Fitzpatrick, 2010; Havnes and Mogstad, 2011; Carta and Rizzica, 2018; Duchini and Van Effenterre, 2024; Kleven et al., 2024; Humphries et al., 2025; Gibbs et al., 2025; Price and Wasserman, 2025).

Much less is known about the role of childcare "quality". While a small literature examines the

effects of pedagogical quality on maternal labor supply (Feldman et al., 2004; Stahl and Schober, 2020), far less attention has been paid to the reliability (i.e., uninterrupted availability) of childcare despite its importance for labor market participation. While a nascent literature examined COVID-induced closures (Albanesi and Kim, 2021; Hansen et al., 2024), those disruptions occurred during a period of global economic shutdown. We complement these studies by identifying a more persistent and idiosyncratic source of disruption. Unlike the pandemic, smoke induced shocks are typically short-lived and occur while the broader labor market remains operational, creating an acute coordination failure for parents. Our findings highlight that the operational reliability of childcare is a critical, yet often overlooked, margin that shapes mothers' long-term labor market trajectories.

Third, we contribute to the literature on the impact of air pollution on labor market outcomes (Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015; Chang et al., 2016; Aragón et al., 2017; Chang et al., 2019; He et al., 2019; Adhvaryu et al., 2022; Borgschulte et al., 2024).[4] This literature documents that air pollution reduces labor productivity and labor supply, with effects that can manifest at the labor market level. Importantly, while most existing studies emphasize workers' own biological responses as the primary mechanism, we show that workers' dual role as caregivers at home can impose as large labor market costs as the biological channel, thereby extending its impacts beyond directly exposed workers.

Lastly, this paper contributes to the literature documenting the gendered impacts of negative environmental shocks. This literature has viewed such shocks largely as a phenomenon in developing countries, where environmental events constitute substantial income shocks affecting outcomes such as girls' education (Björkman-Nyqvist, 2013), child marriage (Corno et al., 2020) and domestic violence (Sekhri and Storeygard, 2014; Díaz and Saldarriaga, 2023). We extend this literature by showing that adverse environmental conditions can exacerbate existing gender gaps even in developed economies.

The rest of the paper proceeds as follows. Section 2 provides conceptual framework. Section 3 provides background on the wildfire smoke and details the data sources. Section 4 describe our estimation framework and Section 5 report results. Section 6 concludes.

[4]For a recent review, see Aguilar-Gomez et al. (2022).

2 Conceptual Framework

To guide the empirical analysis, we develop a simple model illustrating how transitory smoke-driven caregiving shocks can generate persistent reductions in maternal labor supply by eroding current job payoffs and shifting expectations about future caregiving burdens.

Smoke exposure generates stochastic caregiving demand (e.g., school closures or child illness) that must be met either by the mother herself or through alternative arrangements. Let S_t denote the cumulative caregiving burden realized during period t. A mother employed during period t receives flow payoff $u^E(w, S_t) = w - k(S_t) + a(S_t)$, where w denotes earnings over the period.

The term $k(S_t)$ represents the resource cost borne by the worker or household in managing caregiving shocks during the period. This cost is multifaceted and varies across individuals and occupations. It may include pecuniary costs, such as foregone income or emergency childcare expenses, as well as non-pecuniary burdens, such as the mental load of logistics or the social debt incurred when calling in favors from friends and family. While $k(S_t)$ can arise even in self employment that does not involve workplace relationships, the term $a(S_t)$ reflects workplace social capital or match quality, which captures the relational and psychological benefits of being in a supportive and collegial work environment, which enhance job satisfaction. Repeated shocks increase resource costs ($k'(S) \geq 0$) and erode workplace social capital ($a'(S) \leq 0$).

Nonemployment yields constant flow payoff $u^U = b$.[5] Let $\beta \in (0, 1)$ denote the discount factor. Then, the value of employment V^E, equals the sum of the current period payoff and the expected continuation value of employment, as shown in equation (1), where expectation is taken over the probability distribution of future caregiving shocks S_{t+1} conditional on the current state S_t. In particular, following Gallagher (2014), we assume mothers form beliefs about future disruptions based on past realizations, placing higher weight on more recent events. The value of nonemployment is $V^U = b + \beta V^U = \frac{b}{1-\beta}$.

$$V^E(w, S_t) = w - k(S_t) + a(S_t) + \beta \mathbb{E}\Big[\max\{V^E(w, S_{t+1}), V^U\} \mid S_t\Big] \tag{1}$$

The mother re-evaluates the employment decision each period and continues to work if and only if

[5] We abstract from the option value of job search (McCall, 1970), as our empirical findings indicate that smoke-induced separations are primarily driven by transitions out of the labor force rather than into unemployment. Consequently, the outside option is modeled as a state of nonparticipation with a constant flow payoff b.

surplus is nonnegative ($V^E(w, S_t) - V^U \geq 0$). This defines a separation threshold (i.e., reservation wage) $w^R(S_t)$ implicitly by

$$V^E(w^R(S_t), S_t) = V^U, \tag{2}$$

so that the stay condition can be written as $w \geq w^R(S_t)$.

To understand the impact of higher S_t on job exit, we can differentiate equation (1) with S_t. For this, let $V(S_{t+1}) = \max\{V^E(w, S_{t+1}), V^U\}$ denote the mother's optimized value for each realization of S_{t+1} in the next period.

$$\frac{\partial V^E(w, S_t)}{\partial S_t} = \underbrace{-k'(S_t) + a'(S_t)}_{\text{Current Payoff Channel}} + \underbrace{\beta \frac{\partial}{\partial S_t} \mathbb{E}[V(S_{t+1}) \mid S_t]}_{\text{Expectation Channel}} < 0 \tag{3}$$

Equation (3) indicates that an increase in the caregiving burden reduces the current payoff through higher resource costs, $k(S_t)$, and diminished workplace social capital, $a(S_t)$. Further, because the belief process a la Gallagher (2014) implies that a higher current realization S_t shifts the subjective distribution of future shocks S_{t+1} rightward according to first-order stochastic dominance, the continuation value is decreasing in S_t.

The decline in the value of employment translates directly into a higher threshold for staying in the labor force. To see this, we derive $\frac{dw^R(S_t)}{dS_t}$ by invoking the Implicit Function Theorem:

$$\frac{dw^R(S_t)}{dS_t} = -\frac{\partial V^E / \partial S_t}{\partial V^E / \partial w} > 0 \tag{4}$$

Because marginal utility of income $\partial V^E / \partial w$ is positive, the separation threshold $w^R(S_t)$ is strictly increasing in S_t. Mothers therefore require a higher market wage to remain employed as the caregiving burden accumulates, making a separation more likely for any given wage w.

Theory to data. Let wages be distributed according to cumulative distribution function F_W with density f_W. The probability of employment conditional on caregiving shock S is $p(S) = \Pr(w \geq w^R(S)) = 1 - F_W(w^R(S))$ and differentiating yields $\frac{\partial p}{\partial S} = -f_W(w^R(S)) \frac{\partial w^R}{\partial S}$. In the model, S denotes recent caregiving burden. In the data, we operationalize this state as N, the number of smoke days in the past 12 months. This rolling window reflects the idea that the value of employment—shaped by resource costs $k(S)$, workplace social capital $a(S)$, and expectations about future

disruptions—depends primarily on recent caregiving strain rather than more distant shocks. In Section 5, we show that exposures occurring beyond the past year have null effect on employment, supporting this empirical specification. Applying the chain rule yields:

$$\frac{\partial p}{\partial N} = -f_W(w^R(S))\frac{\partial w^R}{\partial S}\frac{\partial S}{\partial N}. \tag{5}$$

Equation (5) shows that the reduced-form employment response reflects three components: the mapping from smoke exposure to caregiving burden $\frac{\partial S}{\partial N}$, the sensitivity of the separation threshold to that burden $\frac{\partial w^R}{\partial S}$, and the mass of workers near the separation margin captured by $f_W(w^R(S))$. Assuming that $\frac{\partial S}{\partial N}$ is similar across individuals, and noting that $f_W(\cdot)$ is common across them, heterogeneity in $\frac{\partial p}{\partial N}$ is governed by differences in $\frac{\partial w^R}{\partial S}$. To characterize moderating factors of the employment response, we approximate equation (4) by assuming $\frac{\partial V^E}{\partial w} \approx 1$ (e.g., under local linearity in wages) and focus on the flow utility representation, which yields:

$$\frac{\partial w^R}{\partial S} \approx k' - a'. \tag{6}$$

Equation (6) highlights two distinct sources of resilience to the shock. The first operates through the marginal resource cost of managing caregiving shock, k', which depends on factors like pay linearity (Goldin, 2014) and access to affordable backup care, including household buffers. The second operates through the marginal erosion of workplace social capital, $-a'$, reflecting how rapidly repeated disruptions strain the employment relationship. While we do not directly observe these primitives, our empirical design allows us to assess their relative importance by examining how variation in factors that plausibly shift each margin moderates the impact of caregiving shocks on employment.

3 Background and Data

3.1 Wildfire Smoke Trends and Impacts

The frequency and intensity of wildfires have increased rapidly due to a changing climate, and in recent years, wildfire emissions have accounted for up to 25% of total $PM_{2.5}$ (particulate matter with aerodynamic diameter $< 2.5, \mu$m) nationwide(Abatzoglou and Williams, 2016; Burke et al., 2021;

Juang et al., 2022). Although wildfire activity is most pronounced in the western US, the impacts of smoke are national in scope due to the long-range transport of emissions from large fires (Burke et al., 2021). Exposure to wildfire smoke is associated with a wide range of adverse health outcomes such as increased respiratory and cardiovascular morbidity, and premature mortality, and has been shown to be particularly harmful for children, whose developing respiratory systems make them more vulnerable to pollution (Gould et al., 2024).

Given these health risks, schools often close in response to severe wildfire smoke events.[6] Indeed, data from California's Department of Education, which will be detailed in Section 3.2, show that wildfire smoke is responsible for 63% of overall school closure days over the 2002–03 to 2018–19 school years.[7] Even when schools remain open, smoke exposure can increase illness among children, raising caregiving needs at home (Heft-Neal et al., 2023).

3.2 Data

Wildfire smoke. We utilize daily, county-level estimates of wildfire smoke–related $PM_{2.5}$ from Childs et al. (2022) for the period 2006–2019. Childs et al. (2022) use a machine-learning model to predict wildfire smoke–attributable $PM_{2.5}$ across the contiguous United States.[8] These data offer important advantages over widely used NOAA Hazard Mapping System data, as they better capture ground-level smoke exposure and provide consistent high-resolution coverage across space and time. The model performs well in predicting observed concentrations ($R^2 = 0.67$; (Childs et al., 2022)) and has been widely adopted in recent wildfire smoke studies (Burke et al., 2023; Wen et al., 2023).

Labor market outcomes. We use data from the Current Population Survey (CPS), a nationally representative household survey that collects labor market outcomes from roughly 60,000 households (about 100,000 individuals) each month. In each monthly survey, households are interviewed about their work-related activities during the reference week, the 7-day calendar week (Sunday–Saturday)

[6] For instance, the California Environmental Protection Agency notes that closing schools during severe wildfire smoke events can protect students by reducing outdoor exposure while traveling to school or moving between buildings on campus, and by preventing heat-related illness when windows must remain closed to keep out smoke (California Environmental Protection Agency, 2019).

[7] Inclement weather and miscellaneous problems (typically school facility failures or student safety issues such as terror threats) explain another 25% and 12% of the closure days.

[8] They first estimate the relationship between observed $PM_{2.5}$ anomalies (defined as increases in $PM_{2.5}$ at EPA monitoring stations on wildfire smoke days from the NOAA Hazard Mapping System) and satellite and meteorological data. The estimated model is then used to generate out-of-sample predictions of wildfire smoke–attributable $PM_{2.5}$.

that includes the 12th of the month.[9] We extract the Basic Monthly CPS data from IPUMS for the 2006–19 period (Flood et al., 2025a), restricting the sample to prime-age civilians (ages 25–54) with youngest child aged between 0 and 17.

The CPS provides information on each respondent's labor market outcomes, including binary indicators for employment status, labor force participation, full-time work, and absenteeism, as well as a continuous measure of actual hours worked during the reference week.[10] It also contains demographic variables such as sex, age, race, educational attainment, industry, occupation, marital status, and the ages of children. Geographic identifiers in the CPS (as well as American Time Use Survey, which is described below) are typically available at the county level; however, for respondents residing in smaller counties (fewer than 100,000 residents), only Core-Based Statistical Area (CBSA) or state identifiers are provided. For 42% of observations with county identifiers, we match individuals to wildfire smoke exposure at the county by month level. For 34% of observations with CBSA identifiers only, we assign the average wildfire smoke level across all counties overlapping that CBSA. Observations identified only at the state level (24%) are removed.[11] Accordingly, while the unit of observation is the individual, the geographic unit at which smoke exposure is measured varies across observations; we refer to this geographic unit as an *area* throughout the paper.

Time use. We extract American Time Use Survey (ATUS) data via IPUMS to supplement our analysis of labor market outcomes (Flood et al., 2025b). ATUS respondents each complete a 24-hour time diary for the day preceding the interview, and the data are provided at the individual level with minute-level information on all activities undertaken during that day. We merge ATUS and wildfire smoke data at the area by day level.

Following Guryan et al. (2008) and Price and Wasserman (2025), we construct measures of childcare time. Specifically, we define primary childcare time as intervals during which the respondent's main activity is childcare.[12] We then compute total childcare by adding the ATUS measure of sec-

[9]The November and December reference weeks are sometimes moved one week earlier so that survey interviewers are not contacting households during major holiday periods. For November, the reference week will be moved one week earlier if Thanksgiving falls during the week that contains the 19th. For December, if the calendar week including the 5th is contained entirely within the month of December, the December reference week will be one week earlier than normal. For more details, see https://www.bls.gov/cps/definitions.htm#refweek (accessed on Oct 20, 2025).

[10]Absenteeism equals one if an employed individual worked zero hours during the reference week (https://www.bls.gov/cps/absences.htm#atworkPT, accessed on Oct 20, 2025).

[11]These shares closely match those reported in Gibson and Shrader (2018).

[12]These activities include basic childcare (e.g., changing diapers), educational childcare (e.g., helping with homework), recreational childcare (e.g., attending a child's sporting event), and travel childcare (e.g., travel related to any of

ondary childcare, defined as time spent providing childcare concurrently with another primary activity. Importantly, the secondary childcare measure is available for parents with children under age 13, and thus our ATUS sample is limited to civilians aged 25–54 with youngest kids aged between 0 and 12, over the period 2006–19.

School closure. We use administrative records of reported school closures from the California Department of Education, compiled by CalMatters through California Public Records Act requests. The dataset documents, for each school that submitted a Form J-13A waiver to protect attendance-based funding, the dates, reasons, and the county of the school's location for closures from the 2002–03 through 2018–19 school years. For the empirical analysis, we aggregate the data to the county-day level and merge it with wildfire smoke exposure at the same spatial and temporal resolution.

Summary statistics. Appendix Table A.1 presents summary statistics for the main analysis sample. Panel A reports labor market outcomes for mothers aged 25–54 whose youngest child is between ages 0 and 17. At the time of the CPS interview, 65.3% of these mothers are employed, 4.2% are unemployed, and the remaining 30.5% are out of the labor force. Among employed mothers (65.3%), 49.6% work full time and 15.7% work part time. Slightly less than half of mothers (42.2%) belong to the treated group—those whose youngest child is aged 5–12—while the remaining 57.8% have either younger or older youngest child. The sample experiences an average of 8.6 smoke days (defined as $PM_{2.5} > 3$) on weekdays in the preceding 12 months. We focus on weekday smoke events because smoke occurring on non-working days is unlikely to have direct labor market impacts.

The last three rows of Panel A report summary statistics for mothers conditional on being employed, which constitute the sample for the contemporaneous effect analyses. Absenteeism—defined as not being present at work for the entire week—averages 4%, and employed mothers work an average of 35 hours per week, while being exposed to wildfire smoke on 0.15 weekdays per week.

Panel B reports school closure outcomes. On a given weekday, the probability of experiencing any school closure at the county level is 0.02, while the probability of being a smoke day is 0.03.

Panel C reports time-use measures from the ATUS. Among employed mothers whose youngest child is aged 0–12, average total childcare time is 418 minutes per day, averaged across weekdays and weekends. Approximately one quarter of this time is devoted to primary childcare, with the

the aforementioned categories). For additional details, see Guryan et al. (2008).

remaining three quarters classified as secondary childcare. These mothers spend, on average, slightly over five hours per day working, corresponding to roughly 35 hours per week. Because secondary childcare is not defined for children older than age 12, the ATUS sample is restricted to mothers whose youngest child is aged 0–12.

4 Empirical Strategy

Our goal is to estimate the impact of wildfire smoke on school closures and subsequent mothers' labor outcomes. We start by estimating a distributed lag model in equation (7) using the California school closure data to investigate the impact of smokes on school operations.

$$Closure_{cdt} = \sum_{k=-10}^{10} \beta^k Smoke_{c,dt-k} + \delta_{cd} + \gamma_{cw} + \theta_t + \epsilon_{cdt} \tag{7}$$

Here, $Closure_{cdt}$ is an indicator equal to 1 if any school in county c was closed on date dt (e.g., Jan 1, 2015). $Smoke_{c,dt-k}$ is an indicator equal to 1 if a wildfire smoke event occurred in county c at relative time k, where k denotes the number of days before ($k < 0$) or after ($k > 0$) date dt. We define a "smoke event" as a day with wildfire-attributable PM2.5 exceeds $3\mu g/m^3$, which corresponds to the average level of increase in PM2.5 observed on wildfire smoke days (Burke et al., 2023).

In equation (7), we include county-by-day-of-year fixed effects (δ_{cd}) to control for location-specific seasonal patterns at a fine daily scale (e.g., Jan 1). County-by-day-of-week fixed effects (γ_{cw}) account for systematic differences across day of week (e.g., Monday), and school-year fixed effects (θ_t) to absorb common annual shocks. β^k captures the dynamic relationship between wildfire smoke occurrence and the likelihood of school closures around smoke events on weekdays. Equation (7) is weighted by county population and standard errors are clustered at the county level.

Identification in equation (7) leverages variation in wildfire smoke exposure, conditional on a rich set of fixed effects. Figure 1 illustrates that county-level exposure to wildfire smoke (i.e., the annual number of weekdays with wildfire attributable PM2.5 exceeding $3\mu g/m^3$) varies substantially across years and regions. This variation primarily reflects the plausibly random spatial and temporal distribution of wildfires and the meteorological conditions that govern smoke transport.

Next, we estimate the impact of wildfire smoke on mothers' labor outcomes operating through

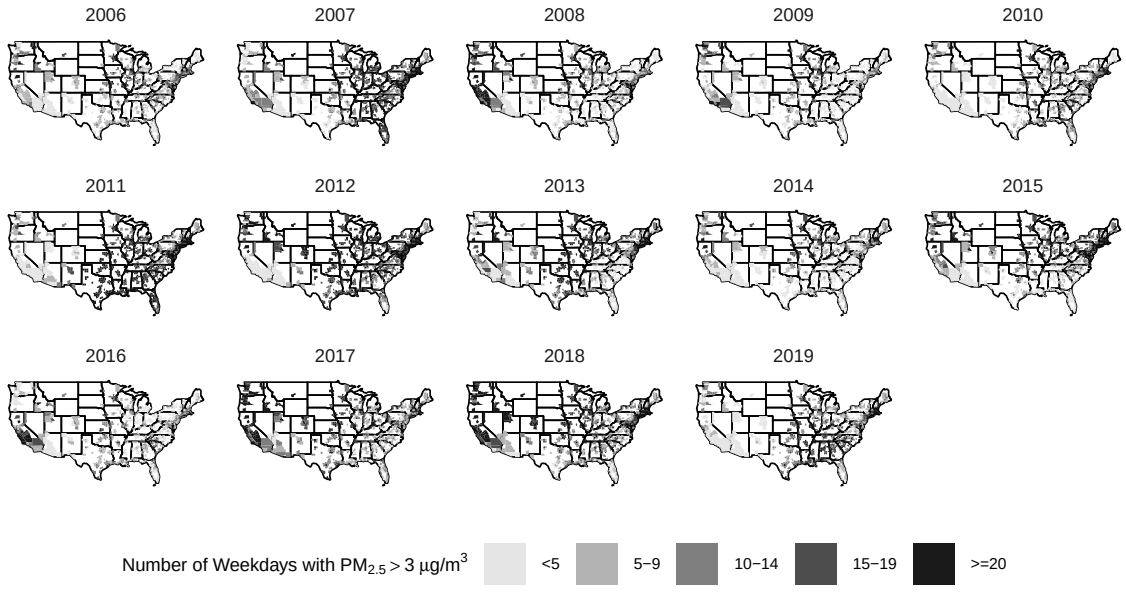


Figure 1: Number of Wildfire Smoke Days by Year. The figure shows the annual number of weekdays with wildfire attributable PM2.5 exceeding $3\mu g/m^3$ for each county. Counties without county or CBSA identifiers in the CPS are displayed in white.

childcare channel. Prior research shows that air pollution affects labor market outcomes through workers' own health, reducing labor supply or productivity (Aguilar-Gomez et al., 2022). To isolate the childcare channel, rather than these direct biological effects, we compare how labor outcomes respond to wildfire smoke for mothers whose youngest child is aged 5–12 (elementary school age) versus mothers whose youngest child is either 0–4 or 13–17.

This choice is guided by baseline time use patterns. Figure 2 plots average time spent on childcare (primary + secondary) by age of the youngest child and by day type (weekday versus weekend). Several patterns emerge. First, average time spent on childcare is substantially higher on weekends than on weekdays — a gap that narrows once the youngest child exceeds age 13, consistent with older children's greater self-sufficiency. Second, the difference in childcare time between weekdays and weekends varies substantially by the age of the youngest child. Specifically, the gap is 190 minutes for mothers whose youngest children are aged 5–12, compared to 99 minutes for those with younger children (0–4), likely reflecting differences in public schooling eligibility. For children older than 13, this gap largely disappears. These patterns suggest that mothers with youngest children aged 5–12 rely most heavily on formal childcare during weekdays and are therefore most likely to experience

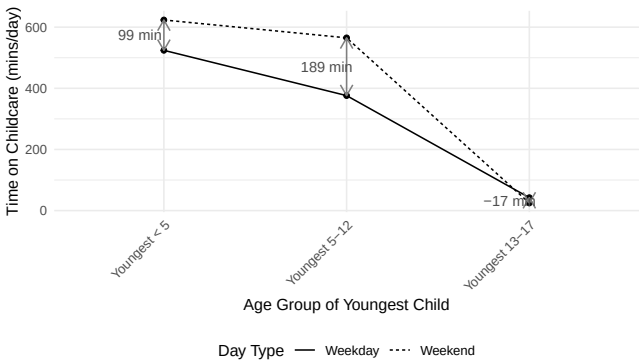


Figure 2: Childcare Time by Age of Youngest Child. This figure shows average childcare time for mothers by age group of the youngest child over the 2006–19 period. Childcare time is the sum of primary and secondary childcare time from ATUS, except for the youngest-child-aged-13–17 group, for whom secondary childcare time is not defined. Averages are calculated using ATUS weights.

work disruptions from smoke driven caregiving shocks, which effectively convert weekdays into weekends in terms of childcare responsibility. Importantly, this pattern holds even when schools remain in session but children cannot attend due to illness.

$$Y_{icsmt} = \beta_1 N_{csmt} + \beta_2 D_i + \beta_3 (N_{csmt} \times D_i) + \mathbf{X}_i + \delta_{cm} + \gamma_{st} + \epsilon_{icsmt} \tag{8}$$

Equation (8) formalizes the identification strategy discussed above. To fix the idea, first consider contemporaneous effect of wildfire smoke. Y_{icsmt} represents labor outcomes such as absenteeism or hours worked during the reference week for individual i in area c, state s, and month–year mt. Our key regressor is $N_{csmt} \times D_i$, an interaction term of the number of wildfire smoke days (PM2.5 $> 3\mu g/m^3$) during the weekday of the reference week and an indicator for "treated" mothers, namely whose youngest child is aged 5–12.[13] We include area-by-month fixed effects (δ_{cm}) to control for local seasonality and state-by-year fixed effects (γ_{st}) to absorb state wide shocks. We also control for individual level covariates ($\mathbf{X}_i$) such as age, education, industry, and race. Importantly, because our contemporaneous analysis focuses on short-term disruptions in work due to wildfire smoke, we exclude individuals who are not employed at the time of survey. The coefficient of interest, β_3, captures the differential effect of wildfire smoke exposure on labor outcomes among mothers most dependent on school-based childcare (those with children aged 5–12) relative to other mothers.

We complement the contemporaneous effect analysis with the ATUS data. While the identification

[13]We show that our results are robust to an alternative definition of treatment, namely having any child aged between 5 and 12.

strategy remains conceptually identical, we adapt equation (8) by replacing N_{csmt} with $Smoke_{csmt}$, an indicator equal to one if the respondent's diary day falls within the "smoke window." This adjustment reflects the temporal structure of the ATUS, which document activities for a single reference day rather than over a week. In practice, we define the smoke window as the period from two days before to five days after a smoke day, corresponding to the range with heightened school-closure probability reported in Figure 3a. Because the ATUS sample is roughly two orders of magnitude smaller than the CPS sample, we use a more parsimonious set of fixed effects (area, month, and year).

Finally, we also estimate the cumulative impact of wildfire smoke on labor outcomes using equation (8) with an important difference: N_{csmt} is the number of wildfire smoke days over the past 12 months. We use a 12-month window to ensure that all observations have a comparable exposure horizon in expectation.[14] Shorter windows (e.g., 3 or 6 months) would make the measure sensitive to the time of year—for example, capturing very few smoke days in winter or overlapping with summer, when many workers are on a vacation for an extended period. In addition, we do not control for industry because, unlike in the contemporaneous specification where industry switching is unlikely, cumulative exposure may influence the types of industries in which individuals are employed.

The key identification assumption for equation (8) is that, absent differential childcare reliance, mothers' labor market responses to wildfire smoke would have been similar across youngest child age groups. That is, the impact of wildfire through own health channel or the impact of local labor demand would have been similar for two different groups of mothers. While this assumption is not directly testable, we run two complementary tests. First, we implement placebo tests by estimating analogous models for groups (e.g., fathers) or time periods (weekends versus weekdays) for which childcare disruptions should be less relevant. Second, in the cumulative exposure specifications, we include leads and lags of smoke exposure, under the conjecture that exposure occurring sufficiently before or after the current period should not affect current periods' labor outcomes.[15]

Importantly, in running these regressions, we exclude mothers working in the elementary and secondary schools, as their responses to smoke-driven school closures (e.g., absenteeism or time uses) are likely mechanical. Our regressions are weighted by relevant CPS or ATUS weights and standard errors are clustered at the area level.

[14] In Section 5, we show that our results are robust to the inclusion of smoke exposure from more distant periods.

[15] Specifically, following Borgschulte et al. (2024), we assign smoke exposure for the same area and calendar month in the years $t-3$, $t-2$, $t-1$, $t+1$, $t+2$, and $t+3$ relative to the current year.

5 Results

5.1 Contemporaneous Impacts of Wildfire Smoke

We begin by examining the first link in equation (5), namely whether wildfire smoke exposure translates into caregiving burden ($\frac{\partial S}{\partial N}$). Specifically, we explore the impact of smoke exposure on school closures, mothers' time use, and workplace absenteeism to establish that exposure generates disruptions consistent with increases in S.

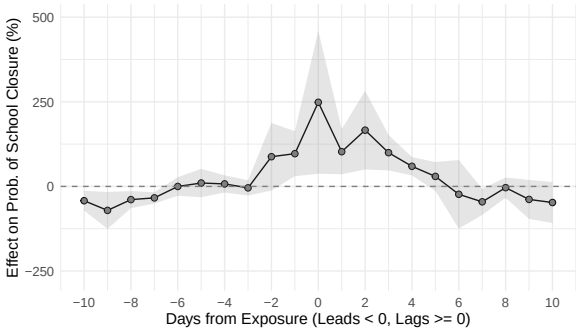
Impact on school closures. Figure 3a reports the estimated coefficients from equation (7), capturing the dynamic effects of wildfire smoke on the likelihood of school closure during the 10 days before and after a smoke day. We find that a smoke day increases the probability of any school closure at the county level by 250% on the day of the event. Moreover, there is substantial temporal spillover: the probability of closure begins to rise two days before the smoke day and remains elevated for up to five days afterward. This pattern likely reflects the strong serial correlation in day-to-day wildfire smoke exposure within locations.[16]

Figure 3b presents estimates from a binned regression examining the relationship between wildfire smoke and school closures, using no-smoke days (wildfire-driven PM2.5 $= 0, \mu g/m^3$) as the omitted category. Even relatively modest smoke exposures lead to substantial increases in the probability of school closure, and the effects rise monotonically with smoke intensity. For days with wildfire-driven PM2.5 $> 7, \mu g/m^3$, the estimated effect corresponds to an increase in closure probability of nearly 750% relative to no-smoke days. Given a baseline closure probability of 2.1% on no-smoke days, this implies a closure probability of over 15% on high-smoke days.

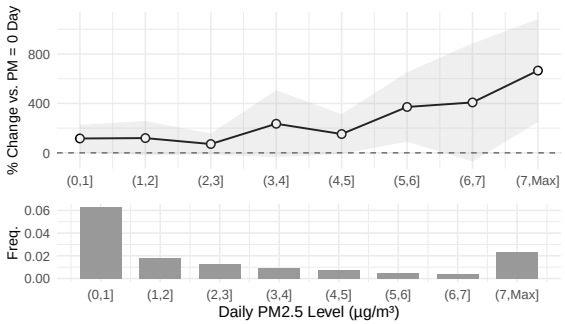
While Figure 3 provides compelling "first-stage" evidence, its findings may not directly generalize to the national level. California, as a wildfire epicenter, may exhibit school responses to smoke that differ from those in other regions. In the absence of comparable administrative school closure data outside California, we turn to CPS data to assess whether similar patterns emerge nationally. Specifically, Appendix Table A.2 estimates a version of equation (8) where N_{csmt} is continue to be the number of wildfire smoke days during the weekday of the reference week and D_i is replaced by a set of categorical indicators for mothers' industries of employment.[17]

[16] The average correlation between $PM_{2.5}$ on consecutive days within the same area is 0.75.

[17] We classify industries into five categories: (1) agriculture, construction, and manufacturing, (2) education, (3)



(a) Wildfire Smoke Impact over Time



(b) Wildfire Smoke Impact by PM Intensity

Figure 3: The Impact of Wildfire Smoke on School Closures. Panel (a) plots the estimated coefficients from equation (7). Panel (b) plots coefficients from a binned regression model with a corresponding frequency histogram of each bin. Bins are created based on the daily wildfire-attributable $PM_{2.5}$ level. In both models, the dependent variable is an indicator for any school closure at the county level, and county-by-day-of-school-year, county-by-day-of-week, and school year fixed effects are included. These regressions are weighted by county population, and grey areas indicate 95 percent confidence intervals based on standard errors clustered on *area*.

If wildfire smoke induces school closures, we would expect a disproportionately large increase in worker absenteeism and a reduction in hours worked among mothers employed in elementary and secondary education. Consistent with this, we find that wildfire smoke has no differential impact on short term labor supply across other industries relative to the omitted category (agriculture, construction, and manufacturing), with the education sector being the only industry exhibiting substantially larger effects. This provides additional support for wildfire smoke's impact on school operations and suggests that the link between wildfire smoke and school disruptions is not unique to California.

Importantly, while these results indicate that school closures are a key source of caregiving shocks from the smoke, they are unlikely to be the only channel. Even when schools remain open, smoke exposure can independently cause disruptions—for example, by increasing child illness and absenteeism—which in turn raises caregiving needs at home (Aguilera et al., 2021; Syed and Basu, 2025).

retail, (4) services, and (5) transportation, communication, utilities, and public sector. In this regression, (1) is the omitted industry category.

Table 1: Wildfire Smokes and Mothers' Time Use (Given Working)

	Weekdays: Yes				Weekdays: No			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var. (Mins/Day):	Total Childcare	Primary Childcare	Secondary Childcare	Working	Total Childcare	Primary Childcare	Secondary Childcare	Working
PM2.5 > 3 Period	-37.41**	-15.72*	-21.70	29.41*	11.61	-18.31*	29.92	0.1221
	(16.83)	(9.222)	(14.56)	(17.22)	(21.39)	(9.983)	(21.72)	(15.63)
Youngest 5-12	-70.51***	-52.22***	-18.29**	34.28***	-20.69*	-70.44***	49.75***	2.743
	(9.310)	(4.260)	(7.231)	(9.154)	(11.44)	(4.077)	(12.35)	(8.342)
PM2.5 > 3 Period x Youngest 5-12	53.18**	2.848	50.33**	-28.61	-9.600	8.996	-18.60	-4.263
	(21.86)	(11.36)	(19.59)	(22.09)	(30.85)	(10.54)	(30.84)	(19.11)
Dep.Var Mean	360.6	113.8	246.8	398.3	556.3	95.34	461.0	113.7
Area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Educ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,076	6,076	6,076	6,076	6,420	6,420	6,420	6,420

Note:
This table reports the effects of wildfire smoke exposure on employed mothers' time use using the American Time Use Survey data over the 2006–19 period. Standard errors clustered at the area level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Impact on mothers' time use. School closures triggered by wildfire smoke have an immediate effect on how employed mothers allocate their time. In Table 1, we examine changes in time spent on childcare and paid work using ATUS data, comparing "treated" mothers—those whose youngest child is aged 5–12 (elementary school age)—to "control" mothers whose youngest child is aged 0–4.[18] To define the period affected by smoke exposure, we draw on the temporal spillover pattern observed in Figure 3a and classify any day within two days before and five days after a smoke day as part of the "smoke period."

Table 1 column (1) indicates that weekday smoke exposure increases total childcare time for treated mothers by 53 minutes (or 14.7%). As shown in columns (2) and (3), this increase is almost entirely driven by a rise in secondary childcare (i.e., supervising children while multitasking) rather than primary childcare. Correspondingly, column (4) shows a 29 minute decline in working time, though this estimate is statistically insignificant. This pattern is consistent with the nature of childcare for elementary school children. Namely, when schools are closed, mothers of elementary school–aged children must provide care, but because these children are relatively independent, much of that care occurs alongside other tasks rather than as dedicated childcare. In contrast, columns (5)–(8) show that wildfire smoke that occurs on weekends does not have a discernible impact on childcare or work time, consistent with the fact that childcare time is already very high (on average over 9 hours) when children are not in school, leaving limited scope for additional increases in measured childcare time.

Impact on contemporaneous labor outcomes. Smoke-driven school closures and the resulting increase in childcare needs are likely to disrupt mothers' work. To assess this, we estimate the effect of wildfire smoke exposure on work absenteeism and hours worked using equation (8) among employed mothers using CPS data.

As shown in Table 2, an additional weekday with wildfire smoke during the CPS reference week raises the probability of work absenteeism by 0.0015 (3.7%) for the treated mothers relative to control mothers. Total hours worked during the reference week also decline by about six minutes (0.3%), consistent with a combination of increased full-week absences and modest reductions in hours among those who continue working. It is worth noting that even though households can adjust along mul-

[18] Since the secondary childcare time variable is not defined for children older than 13, we restrict the ATUS analysis to mothers whose youngest child is aged between 0 and 12.

Table 2: Contemporaneous Effect of Wildfire Smoke on Labor Outcomes (Given Working)

	(1)	(2)
Dependent Var.:	Absent	Hrs Worked
N PM2.5 > 3 (Weekly)	-0.0011*	0.0523
	(0.0007)	(0.0366)
Youngest 5-12	-0.0147***	0.4807***
	(0.0006)	(0.0515)
N PM2.5 > 3 (Weekly) x Youngest 5-12	0.0015*	-0.1019*
	(0.0009)	(0.0566)
Dep.Var Mean	0.0406	34.74
Area × Month FE	Yes	Yes
State × Year FE	Yes	Yes
Race FE	Yes	Yes
Educ FE	Yes	Yes
Age FE	Yes	Yes
Industry FE	Yes	Yes
Observations	1,049,006	1,049,006

Note:
This table reports the contemporaneous effects of wildfire smoke on employed mother worker's hours worked and the probability of absenteeism during the CPS reference week. We use CPS monthly data from 2006–2019, conditional on being employed. Standard errors are clustered at the area level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

tiple margins (e.g., paying for emergency care or relying on social networks to remain at work that day), smoke driven caregiving shocks lead to observable labor supply reductions, indicating substantive disruptions for the average treated mother.

In Appendix Table A.3 we repeat Table 2 for employed fathers. We find that one additional smoke day during the CPS reference week increases absenteeism by 0.0012 but it has no discernible impact on hours worked (if anything, a small positive impact). These findings are consistent with a small subset of fathers share short-term childcare burden by missing work entirely, most fathers do not adjust their work hours in response to smoke induced disruptions.

Table 3: Cumulative Effect of Wildfire Smoke on Labor Outcomes

	(1)	(2)	(3)	(4)	(5)
Dependent Var.:	Employed	Unemp.	Not In LF	Full-Time	Part-Time
N PM2.5 > 3	0.0002	-6.81e-5	-0.0001	0.0002	2e-5
	(0.0002)	(7.21e-5)	(0.0002)	(0.0002)	(0.0001)
Youngest 5-12	0.0398***	0.0048***	-0.0446***	0.0268***	0.0130***
	(0.0033)	(0.0009)	(0.0031)	(0.0035)	(0.0018)
N PM2.5 > 3 x Youngest 5-12	-0.0007***	0.0001	0.0006***	-0.0006**	-0.0002
	(0.0002)	(8.21e-5)	(0.0002)	(0.0003)	(0.0002)
Dep.Var Mean	0.6532	0.0420	0.3048	0.4960	0.1572
Area × Month FE	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes
Educ FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Observations	1,455,192	1,455,192	1,455,192	1,455,192	1,455,192

Note:
This table reports the effects of cumulative wildfire smoke exposure on mothers' labor outcomes. We use CPS monthly data for the 2006–19 period. Standard errors are clustered at the area level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

5.2 Cumulative Impacts of Wildfire Smoke

Main effects. Having established that wildfire smoke exposure generates caregiving burden, we next estimate the impact of cumulative smoke exposure on employment probability. In Table 3, column (1) shows that one additional weekday smoke day in the past 12 months reduces the probability of being employed by 0.0007 (or 0.11%). Equation (5) suggests that this reduced-form estimate reflects the combined effect of exposure on caregiving burden ($\frac{\partial S}{\partial N}$) and the resulting shift in the separation threshold ($\frac{\partial W^R}{\partial S}$), scaled by the density of workers near the separation threshold ($-f_W(w^R(S))$).

Comparing columns (2) and (3) indicates that this reduction is driven primarily by mothers exiting the labor force rather than becoming unemployed. Likewise, columns (4) and (5) show that the decline in employment is concentrated among full-time positions, with little change in part-time work. This pattern suggests that wildfire smoke exposure not only disrupts current employment but may also contribute to longer-term detachment from the labor market, as affected mothers scale back or withdraw from full-time work.

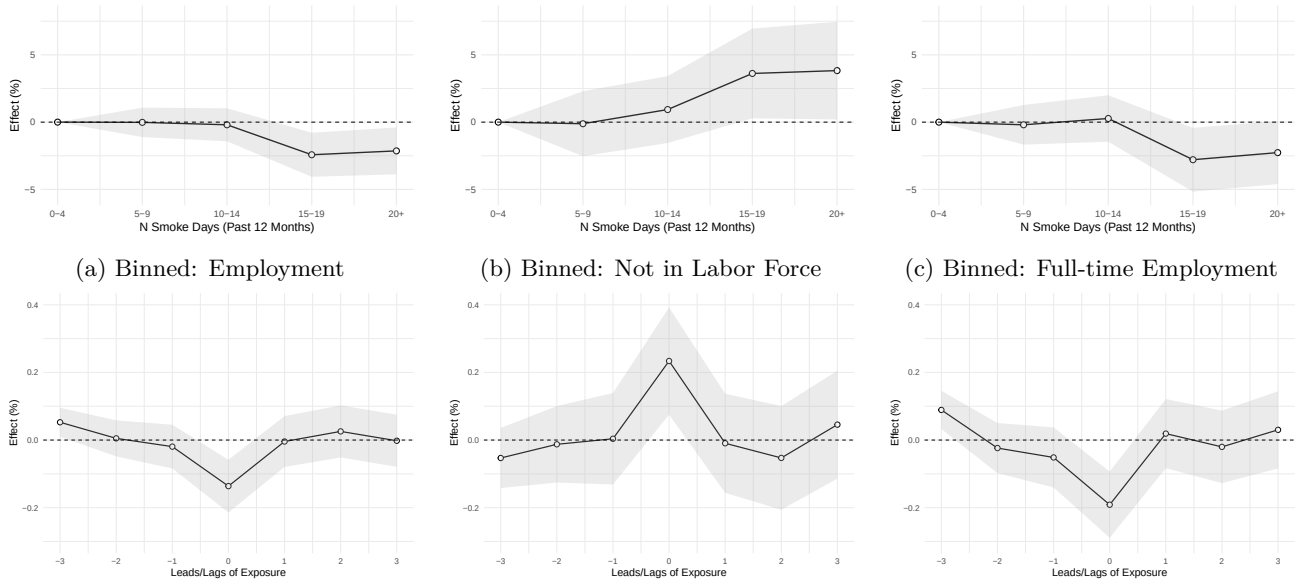
How large is the effect size? An average mother in our sample experiences 8.6 weekdays with wildfire smoke per year, which implies roughly a 1% decline in employment probability among treated mothers. While modest in magnitude, this effect suggests that unexpected caregiving shocks can meaningfully erode the maternal employment gains associated with formal childcare availability. Indeed, many studies evaluating childcare expansions in developed countries—including Australia (Kleven et al., 2024), France (Goux and Maurin, 2010), Norway (Havnes and Mogstad, 2011), Spain (Nollenberger and Rodríguez-Planas, 2015), and the United States (Fitzpatrick, 2010, 2012)—find small and statistically insignificant effects on maternal employment, often attributed to substitution from informal care or preferences for maternal care.[19] [20]

Having established the main effect, we next investigate the nature of the dose (exposure)–response relationship along three dimensions: temporal horizon over which exposure matters, the relative importance of shock frequency versus duration, and the linearity of the marginal employment response. In Appendix Table A.5, we augment the baseline specification by including smoke exposure from the past 13–24 and 25–36 months, along with their interactions with the treated group indicator. We find that, conditional on exposure in the past 12 months, earlier exposure has a precisely estimated null effect on employment. This is consistent with our modeling assumption in Section 2 that, once conditioning on recent caregiving burden, more distant past is irrelevant for employment decisions.

We next ask which form of recent exposure matters. A given total number of smoke days in the past 12 months can arise from a single prolonged episode or multiple short ones—two forms of exposure with a priori ambiguous implications for labor market outcomes. To assess their relative importance, we decompose total exposure in the past 12 months into (i) the number of distinct smoke episodes and (ii) the average duration of those episodes, and estimate their respective impacts on labor outcomes. Appendix Table A.6 shows that the number of independent episodes is the primary driver, suggesting that repeated disruptions to caregiving arrangements—rather than the duration of

[19] Some studies find larger effects in specific settings, such as Canada (Baker et al., 2008) and Norway (Andresen and Havnes, 2019).

[20] Our estimates also shed light on the relative importance of the physiological versus caregiving channels through which wildfire smoke affects labor market outcomes. Borgschulte et al. (2024) find that one additional smoke day in a quarter reduces employment by 0.013%. To facilitate comparison, we reproduce Table 3 using a smoke day threshold consistent with their definition—wildfire-driven $PM_{2.5}$ exceeding $1\mu g/m^3$—in Appendix Table A.4. The estimate indicates that one additional weekday smoke day in the past 12 months reduces employment among treated mothers by 0.044%. Applying a simple linear scaling to the estimate in Borgschulte et al. (2024) implies an annualized employment effect of roughly 0.052%, suggesting that the caregiving channel may generate labor market impacts comparable in magnitude to the direct physiological effects.



(a) Binned: Employment (b) Binned: Not in Labor Force (c) Binned: Full-time Employment

(d) Dynamic: Employment (e) Dynamic: Not in Labor Force (f) Dynamic: Full-time Employment

Figure 4: The Cumulative Impact of Wildfire Smoke on Maternal Labor Supply. Panels (a)-(c) plot coefficients from a binned regression version of equation (8), while panels (d)-(f) plot coefficients from a version of equation (8) with three leads and lags of smoke exposure, both capturing the cumulative impact of wildfire smoke on maternal labor supply. Dependent variables are indicators for employment, non-participation in the labor force, and full-time employment. Grey areas represent 95 percent confidence intervals based on standard errors clustered at the area level.

any single episode—are most strongly associated with maternal job exit.

Finally, in Figures 4a–4c, we investigate the shape of the dose-response function by relaxing the linear marginal effect assumption implicit in equation (8). We replace the continuous exposure measure with five indicator variables for the number of weekday smoke events in the past 12 months: 0–4, 5–9, 10–14, 15–19, and 20+. The estimated coefficients show that fewer than 15 smoke days does not meaningfully affect labor outcomes. However, exceeding two weeks of smoke days leads to a sharp 2.5% reduction in employment and full-time employment probability, while increasing the probability of not being in the labor force by over 3%, with the effect remaining stable beyond 20 days. These patterns suggest a threshold in the dose-response relationship: modest caregiving disruptions can be absorbed without persistent labor market consequences, whereas sufficiently frequent shocks trigger discrete extensive-margin exits.

Table 4: Cumulative Impact of Wildfire Smoke on the Prob. of Employed (Heterogeneous Effects)

	Resource Cost (k)				Workplace Social Capital (a)	
	Nonworking Adult in HH		Occ. Substitutability		Industry % Female	
	Yes	No	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.:	Employed	Employed	Employed	Employed	Employed	Employed
N PM2.5 > 3	0.0003	0.0001	0.0002	0.0001	-7.92e-6	0.0003**
	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Youngest 5-12	0.0100*	0.0479***	0.0014	-0.0011	-0.0042**	0.0040*
	(0.0060)	(0.0038)	(0.0024)	(0.0015)	(0.0021)	(0.0021)
N PM2.5 > 3 x Youngest 5-12	-0.0010**	-0.0008***	-0.0004	-0.0001	9.87e-5	-0.0006***
	(0.0005)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Dep.Var Mean	0.9380	0.9302	0.9110	0.9581	0.6201	0.7146
Area × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes
Educ FE	No	No	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	381,970	1,073,222	510,839	503,036	514,907	516,302

Note:
This table reports the heterogeneous effects of cumulative wildfire smoke exposure on mother workers' probability of employed at the time of CPS reference week. Each column presents estimates from equation (8) for different subsamples. Standard errors are clustered at the area level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Determinants of the effect size. Theoretical predictions in Section 2 imply that the impact of caregiving burden on employment outcomes can vary substantially by job and worker characteristics. In Table 4, we estimate equation (8) separately by determinants of resource costs (k' in equation (6)) and workplace social capital (a' in equation (6)).[21]

In columns (1) and (2), we estimate equation (8) separately by whether a non-working adult resides in the household—a factor that can reduce the resource cost of caregiving shocks, as affected mothers may be able to rely on backup care at a cost below market alternatives. The results indicate that having a non-working adult at home does not moderate the impact of smoke exposure on employment: if anything, the point estimate is slightly larger. In columns (3) and (4), we estimate equation (8) separately by another determinant of k': the degree of substitutability between workers. This distinction is motivated by Goldin (2014), which documents substantial earnings penalties for reduced hours in occupations where worker substitutability is low. To classify occupations by substitutability, we follow Goldin (2014) and use measures constructed from O*NET data. The results show that above-median substitutability does not mitigate the negative impact of caregiving shocks on employment: indeed, the point estimate is larger in magnitude for higher-substitutability occupations, though both coefficients are statistically insignificant. Taken together, these results suggest that lower k' does not shield mothers from smoke-driven job exit.

In columns (5) and (6), we repeat the same exercise using female industry share as a proxy for a', the rate at which workplace social capital erodes due to caregiving shocks. In industries with high female shares, workplace cultures are more likely to be forgiving of work disruptions due to caregiving shocks, lowering a'. Indeed, the estimated coefficients show that working in an above-median female share industry completely negates the negative impact of caregiving shocks on employment, while employment probability falls by 0.0006 in below-median female share industries in response to one additional weekday smoke events in the past 12 months. Moreover, as Appendix Table A.7 shows, these results hold even after conditioning on occupational substitutability: female industry share mitigates the negative impact of caregiving shocks within both high- and low-substitutability occupations. These findings are consistent with the interpretation that workplace culture that tolerates

[21] In practice, these margins may interact—for example, access to backup care can reduce the need for workplace absences, while accommodating workplaces may reduce reliance on backup care—so realized costs along the two channels may be correlated. We therefore classify factors based on the margin they most directly shift and use heterogeneity in these factors to assess their relative importance.

unpredictability is an important moderator of smoke-driven job exit.

Importantly, results based on occupation or industry classifications (i.e., columns (3)–(6)) should be interpreted with caution, as they capture only transitions from employment to unemployment and do not capture transitions out of the labor force due to CPS data limitations.[22]

Robustness checks. We assess the robustness of our findings in several ways. First, in Figures 4d–4f, we estimate a dynamic version of equation (8) as a placebo test. Specifically, we test whether smoke exposure occurring before or after year t predicts labor outcomes in year t. We find that weekday smoke exposure accumulated over the prior 12 months (event year 0) has a substantial effect on labor outcomes, with magnitudes closely corresponding to those reported in Table 3. In contrast, the coefficients on future exposure (event years 1 to 3) are close to zero, indicating that smoke exposure in subsequent years does not affect current labor outcomes. Similarly, coefficients on earlier exposure (event years 1 to 3) are small and statistically indistinguishable from zero, suggesting no evidence of differential pre-trends between treated and control mothers prior to smoke exposure.

Second, Appendix Figure A.1 examines the sensitivity of our results to alternative definitions of a smoke day. Specifically, we vary the threshold for wildfire-driven $PM_{2.5}$ concentrations, defining smoke days as those exceeding 1, 3, 6, and 9 $\mu g/m^3$, respectively. Consistent with the intuition that higher treatment intensity should generate larger effects, we find a monotonically increasing relationship between the stringency of the smoke day definition and the estimated impact. For example, the effect of one additional smoke day on employment is estimated at –0.004, –0.007, –0.01, and –0.01, respectively, across the four thresholds—all of which are statistically significant. A similar pattern holds for full-time employment and labor force participation as well.

Third, in Appendix Table A.8, we implement a placebo test using fathers. Consistent with the literature documenting limited paternal responses to caregiving shocks (Kleven et al., 2019; Hansen et al., 2024), we find precisely estimated null effects on employment, labor force participation, and full- and part-time employment probabilities. This strengthens the interpretation that the effects for mothers reflect increased caregiving demand arising from smoke-driven school closures rather than general labor market conditions.

Lastly, Appendix Table A.9 shows that that our findings are robust to an alternative definition of

[22]This is because occupation or industry codes are not available for respondents who are no longer in the labor force.

treatment, namely having *any* child aged between 5–12.

6 Conclusion

This paper shows that even when formal childcare and public schooling are widely available, mothers' labor market outcomes may remain vulnerable to stochastic caregiving disruptions. Using plausibly exogenous variation in wildfire smoke exposure, we document that smoke disrupts school operations, and this imposes immediate utility costs on employed mothers who are most reliant on schools for childcare. These costs accumulate over time, reducing affected mothers' employment probability by 1% at the mean smoke exposure level. Given that numerous prior studies find small or null effects of childcare expansion on maternal employment, a 1% reduction from disruptions alone represents a substantial offset of the gains from increased childcare availability. We further show that workplace cultures that tolerate unpredictability can play an important role in moderating the effect of caregiving shocks on job exit.

These findings suggest that the effectiveness of formal childcare institutions depends not only on access but also on their reliability. As environmental shocks such as wildfire smokes are projected to increase in frequency and severity with climate change, the vulnerability of mothers' labor market attachment to caregiving disruptions is likely to grow. Policies that reduce the frequency of such shocks or encourage more accommodating workplace cultures therefore play an important role in sustaining mothers' labor market attachment.

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A Additional Tables and Figures

Table A.1: Descriptive Statistics

Variables	Min.	Max.	Median	Mean	Std.Dev.	N
Panel A: Monthly CPS						
Employed	0	1	1	0.653	0.473	1,455,192
Unemployed	0	1	0	0.042	0.199	1,455,192
Not In Labor Force (NILF)	0	1	0	0.305	0.456	1,455,192
Employed: Full-Time	0	1	1	0.496	0.5	1,455,192
Employed: Part-Time	0	1	0	0.157	0.369	1,455,192
Youngest: 0-4	0	1	0	0.365	0.48	1,455,192
Youngest: 5-12	0	1	0	0.422	0.494	1,455,192
Youngest: 13-17	0	1	0	0.213	0.412	1,455,192
Has a College Degree	0	1	0	0.351	0.48	1,455,192
Union Coverage	0	1	0	0.05	0.111	1,455,192
N PM2.5 $>$ 3 (Past 12 Mon)	0	60	7	8.6	7	1,455,192
Absenteeism (Given Working)	0	1	0	0.041	0.198	1,049,006
Hours Worked (Given Working)	0	168	40	34.7	13.7	1,049,006
N PM2.5 $>$ 3 (Weekly)	0	5	0	0.147	0.561	1,049,006
Panel B: School Closures						
Any School Closure	0	1	0	0.023	0.115	196,739
If PM2.5 $>$ 3	0	1	0	0.027	0.216	196,739
Panel C: ATUS (Unit: Mins/Day)						
Total Childcare Time	0	1,300	440	418	291	12,496
Primary Childcare Time	0	1,140	71	108	117	12,496
Secondary Childcare Time	0	1,290	315	310	273	12,496
Work Time	0	1,380	148	315	267	12,496

Table A.2: Wildfire Smoke and Contemporaneous Labor Outcomes by Industry

	(1)	(2)
Dependent Var.:	Absent	Hrs Worked
N PM2.5 > 3 (Weekly)	-0.0045***	0.2856***
	(0.0013)	(0.0900)
Ind:Educ	0.0791***	-5.383***
	(0.0019)	(0.1771)
Retail	0.0031***	-3.181***
	(0.0010)	(0.1246)
Services	0.0035***	-2.433***
	(0.0009)	(0.1111)
TCU/Public	0.0052***	-0.5344***
	(0.0013)	(0.1204)
N PM2.5 > 3 (Weekly) x Ind:Educ	0.0402***	-1.610***
	(0.0046)	(0.2215)
N PM2.5 > 3 (Weekly) x Retail	-0.0017	-0.0767
	(0.0015)	(0.1027)
N PM2.5 > 3 (Weekly) x Services	-0.0006	-0.1284
	(0.0013)	(0.0936)
N PM2.5 > 3 (Weekly) x TCU/Public	-0.0021	0.0801
	(0.0020)	(0.1220)
Area × Month FE	Yes	Yes
State × Year FE	Yes	Yes
Race FE	Yes	Yes
Educ FE	Yes	Yes
Age FE	Yes	Yes
Observations	1,183,219	1,183,219

Note:
This table reports the contemporaneous effects of wildfire smoke on mother worker's hours worked and the probability of absenteeism during the CPS reference week by industry. We use CPS monthly data for the 2006–19 period conditional on working. Standard errors are clustered at the area level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.3: Contemporaneous Effect of Wildfire Smoke on Fathers' Labor Outcomes (Given Working)

	(1)	(2)
Dependent Var.:	Absent	Hrs Worked
N PM2.5 > 3 (Weekly)	-0.0007*	0.0073
	(0.0004)	(0.0352)
Youngest 5-12	-0.0016***	0.1065**
	(0.0004)	(0.0450)
N PM2.5 > 3 (Weekly) x Youngest 5-12	0.0012**	0.0125
	(0.0006)	(0.0471)
Dep.Var Mean	0.0240	42.30
Area × Month FE	Yes	Yes
State × Year FE	Yes	Yes
Race FE	Yes	Yes
Educ FE	Yes	Yes
Age FE	Yes	Yes
Industry FE	Yes	Yes
Observations	1,183,188	1,183,188

Note:
This table reports the contemporaneous effects of wildfire smoke on emplyed father worker's hours worked and the probability of absenteeism during the CPS reference week. We use CPS monthly data from 2006–2019, conditional on being employed. Standard errors are clustered at the area level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.4: Cumulative Effect of Wildfire Smoke on Labor Outcomes (Alt. Threshold)

	(1)	(2)	(3)	(4)	(5)
Dependent Var.:	Employed	Unemp.	Not In LF	Full-Time	Part-Time
N PM2.5 > 1	6.79e-5	-1.56e-5	-5.22e-5	9.27e-5	-2.49e-5
	(0.0001)	(5.39e-5)	(0.0001)	(0.0001)	(9.87e-5)
Youngest 5-12	0.0398***	0.0047***	-0.0445***	0.0259***	0.0139***
	(0.0035)	(0.0010)	(0.0034)	(0.0038)	(0.0021)
N PM2.5 > 1 x Youngest 5-12	-0.0004***	7.84e-5	0.0004**	-0.0003	-0.0002
	(0.0002)	(5.43e-5)	(0.0002)	(0.0002)	(0.0001)
Dep.Var Mean	0.6532	0.0420	0.3048	0.4960	0.1572
Area × Month FE	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes
Educ FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Observations	1,455,192	1,455,192	1,455,192	1,455,192	1,455,192

Note:
This table reports the effects of cumulative wildfire smoke exposure on mothers' labor outcomes. We use CPS monthly data for the 2006–19 period. Standard errors are clustered at the area level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.5: Cumulative Effect of Wildfire Smoke on Labor Outcomes (Longer Horizon)

	(1)	(2)	(3)
Dependent Var.:	Employed	Not In LF	Full-Time
Youngest 5-12	0.0376***	-0.0423***	0.0266***
	(0.0044)	(0.0040)	(0.0046)
N PM2.5 > 3 (Past 12 Months)	0.0002	-0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)
N PM2.5 > 3 (Past 13-24 Months)	0.0005**	-0.0004**	0.0004*
	(0.0002)	(0.0002)	(0.0002)
N PM2.5 > 3 (Past 25-36 Months)	0.0003	-0.0004*	0.0003
	(0.0002)	(0.0002)	(0.0002)
Youngest 5-12 x N PM2.5 > 3 (Past 12 Months)	-0.0007***	0.0006**	-0.0006**
	(0.0002)	(0.0002)	(0.0002)
Youngest 5-12 x N PM2.5 > 3 (Past 13-24 Months)	-4.79e-5	-1.39e-5	-4.78e-5
	(0.0002)	(0.0002)	(0.0002)
Youngest 5-12 x N PM2.5 > 3 (Past 25-36 Months)	0.0001	-0.0001	-5.11e-5
	(0.0003)	(0.0003)	(0.0003)
Dep.Var Mean	0.6532	0.3048	0.4960
Area × Month FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Race FE	Yes	Yes	Yes
Educ FE	Yes	Yes	Yes
Age FE	Yes	Yes	Yes
Observations	1,223,451	1,223,451	1,223,451

Note:
This table reports the effects of cumulative wildfire smoke exposure on mothers' labor outcomes based on an alternative specification (including longer time horizon for smoke exposure). We use CPS monthly data for the 2006–19 period. Standard errors are clustered at the area level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.6: Cumulative Effect of Wildfire Smoke on Labor Outcomes (Episodes)

	(1)	(2)	(3)	(4)	(5)
Dependent Var.:	Employed	Unemp.	Not In LF	Full-Time	Part-Time
N PM2.5 > 3 Episodes	0.0003	-0.0002*	-9.4e-5	0.0004	-8.59e-5
	(0.0004)	(0.0001)	(0.0003)	(0.0004)	(0.0003)
Youngest 5-12	0.0390***	0.0053***	-0.0443***	0.0227***	0.0163***
	(0.0063)	(0.0020)	(0.0060)	(0.0067)	(0.0039)
Avg Duration of PM2.5 > 3 Episodes	-0.0015	0.0008	0.0008	-0.0023	0.0007
	(0.0028)	(0.0011)	(0.0028)	(0.0030)	(0.0019)
Avg PM of PM2.5 > 3 Episodes	0.0086	-0.0028	-0.0058	0.0087	-0.0001
	(0.0109)	(0.0032)	(0.0110)	(0.0114)	(0.0062)
N PM2.5 > 3 Episodes x Youngest 5-12	-0.0013***	0.0004***	0.0009*	-0.0010**	-0.0003
	(0.0005)	(0.0002)	(0.0005)	(0.0005)	(0.0003)
Avg Duration of PM2.5 > 3 Episodes × Youngest 5-12	0.0007	-0.0012	0.0005	0.0043	-0.0036
	(0.0042)	(0.0014)	(0.0042)	(0.0044)	(0.0028)
Avg PM of PM2.5 > 3 Episodes × Youngest 5-12	0.0014	-0.0003	-0.0011	-0.0167	0.0181
	(0.0153)	(0.0043)	(0.0157)	(0.0156)	(0.0124)
Dep.Var Mean	0.6532	0.0420	0.3048	0.4960	0.1572
Area × Month FE	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes
Educ FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Observations	1,384,756	1,384,756	1,384,756	1,384,756	1,384,756

Note:
This table reports estimates of the effects of cumulative wildfire smoke exposure, decomposed into smoke duration and smoke episodes, on mothers' labor outcomes during the CPS reference week. Standard errors are clustered at the area level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

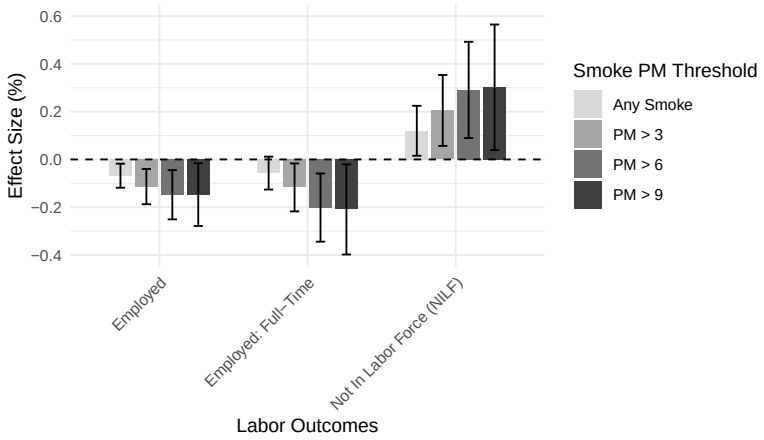


Figure A.1: Sensitivity Analysis. This figure plots the cumulative impact of smoke exposure on treated mothers using equation (8) based on alternative definitions (i.e., thresholds) of smoke days.

Table A.7: Cumulative Impact of Wildfire Smoke on the Prob. of Employed (by Female Share and Substitutability)

	Substitutability: Low		Substitutability: High	
	% Female: High	% Female: Low	% Female: High	% Female: Low
	(1)	(2)	(3)	(4)
Dependent Var.:	Employed	Employed	Employed	Employed
N PM2.5 > 3	-9.82e-5	0.0004*	9.96e-5	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Youngest 5-12	-0.0056*	0.0076**	-0.0033	0.0014
	(0.0033)	(0.0032)	(0.0022)	(0.0025)
N PM2.5 > 3 x Youngest 5-12	0.0003	-0.0009***	4.28e-6	-0.0003
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Dep.Var Mean	0.9141	0.9080	0.9623	0.9537
Area × Month FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
Educ FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Observations	253,130	257,709	253,817	249,219

Note:
This table reports the heterogeneous effects of cumulative wildfire smoke exposure on mother workers' probability of employed at the time of CPS reference week. Each column presents estimates from equation (8) for different subsamples. Standard errors are clustered at the area level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.8: Cumulative Effect of Wildfire Smoke on Labor Outcomes (Fathers)

	(1)	(2)	(3)	(4)	(5)
Dependent Var.:	Employed	Unemp.	Not In LF	Full-Time	Part-Time
N PM2.5 > 3	0.0003**	-0.0003***	-6.94e-5	0.0004***	-7.98e-5
	(0.0001)	(8.42e-5)	(9.64e-5)	(0.0002)	(8.05e-5)
Youngest 5-12	0.0022	0.0003	-0.0025*	0.0028	-0.0006
	(0.0019)	(0.0012)	(0.0014)	(0.0019)	(0.0012)
N PM2.5 > 3 x Youngest 5-12	-4.44e-5	0.0002*	-0.0001	-7.05e-6	-3.73e-5
	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Dep.Var Mean	0.9020	0.0412	0.0568	0.8615	0.0406
Area × Month FE	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes
Educ FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Observations	1,200,200	1,200,200	1,200,200	1,200,200	1,200,200

Note:
This table reports the effects of cumulative wildfire smoke exposure on fathers' labor outcomes. We use CPS monthly data for the 2006–19 period. Standard errors are clustered at the area level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.9: Cumulative Effect of Wildfire Smoke on Labor Outcomes (Alt. Treatment Definition)

	(1)	(2)	(3)	(4)	(5)
Dependent Var.:	Employed	Unemp.	Not In LF	Full-Time	Part-Time
N PM2.5 > 3	0.0004*	-0.0002**	-0.0002	0.0005**	-0.0001
	(0.0002)	(8.33e-5)	(0.0002)	(0.0002)	(0.0002)
Any 5-12	-0.0296***	0.0018*	0.0278***	-0.0437***	0.0140***
	(0.0028)	(0.0010)	(0.0028)	(0.0034)	(0.0021)
N PM2.5 > 3 x Any 5-12	-0.0008***	0.0002**	0.0006**	-0.0009***	0.0001
	(0.0003)	(8.52e-5)	(0.0002)	(0.0003)	(0.0002)
Dep.Var Mean	0.6532	0.0420	0.3048	0.4960	0.1572
Area × Month FE	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes
Educ FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Observations	1,455,192	1,455,192	1,455,192	1,455,192	1,455,192

Note:
This table reports the effects of cumulative wildfire smoke exposure on mothers' labor outcomes based on an alternative treatment group definition (having any child aged 5-12). We use CPS monthly data for the 2006–19 period. Standard errors are clustered at the area level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.