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Air pollution from agricultural fires increases hypertension risk☆

Hemant K. Pullabhotla [a,1], Mateus Souza [b,*]

[a] Center on Food Security and the Environment, Stanford University, Stanford, CA 94305, USA
[b] Department of Economics, Universidad Carlos III de Madrid, Calle Madrid, 126, Getafe, Madrid 28903, Spain

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ABSTRACT

In many parts of the developing world, farmers widely use deliberate fires to burn vegetation and clear land to plant crops. These agricultural fires, however, are known to be associated with health costs due to increased air pollution. We contribute to underpinning the associated health cost estimates by studying the effects of these fires on hypertension risk. Despite being one of the leading causes of mortality globally, there is little direct evidence on how hypertension risk changes with exposure to pollution from agricultural fires. To overcome common data and empirical challenges in this setting, we match blood pressure readings from nearly 784,000 individuals across India with satellite data on 1.2 million agricultural fires, wind direction realizations, and local ambient air pollution. We find that the incidence of hypertension increases by 1.8% for each standard deviation increase in the number of upwind fires observed one day before the blood pressure readings. We find that the impact is stronger among older males, smokers, individuals that were already on blood pressure medication, and individuals belonging to socially marginalized groups. Our estimates suggest that agricultural fires in India lead to hypertension-related additional mortality, associated with USD 9 billion annually in costs.

1. Introduction

The global costs of ambient air pollution amount to $6.43 trillion annually, according to recent estimates (World Bank, 2022). Underpinning these estimates are two key components: the value of a statistical life (VSL) and the magnitude of the impact of air pollution on health. Focusing on the latter, an extensive body of work has found adverse effects of air pollution, such as the increased risk of mortality amongst children and adults,[2] and reduced birth weights (Yang and Chou, 2018; Jones and Berrens, 2021). However, it is unclear whether estimates from these prior studies are applicable globally, across diverse contexts and different sources of pollution. For example, recent meta-analyses reveal that most of the existing studies are confined to high-income countries, with little coverage of South Asia, Africa, or Latin America (Orellano et al., 2020; Yang et al., 2018; Choi et al., 2019). Extrapolating the concentration–response relations found in developed countries to low-income regions may be problematic given the differences in access to healthcare, dietary and occupational patterns, as well as the much higher levels of ambient air pollution in the developing world (Arceo et al., 2016). Epidemiological evidence also suggests that health damages vary by air pollution source and composition

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* Corresponding author.
E-mail addresses: h.pullabhotla@deakin.edu.au (H.K. Pullabhotla), mateus.nogueira@uc3m.es (M. Souza).

1 Department of Economics, Deakin University, Victoria, 3125, Australia.

2 For example, see: Chay and Greenstone, 2003; Currie et al., 2014; Deryugina et al., 2019; Wu et al., 2020.

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(World Bank, 2022; Brook et al., 2010). However, most empirical studies focus on emissions from urban or industrial sources, with limited attention given to the effects of polluting sources in rural areas. Accurate quantification of the costs of air pollution, and thus the quantification of potential benefits from its abatement, necessarily needs to account for these sources of heterogeneity.

A key challenge limiting the coverage of past studies has been the paucity of air pollution and health data in developing countries, particularly in rural areas. Coverage of air pollution monitors is sparse in many developing countries and limited to large cities or close to industrial areas (Graff Zivin and Neidell, 2013). As a result, evidence on the impact of significant non-urban sources of pollution such as biomass burning, common across rural areas, is minimal. A second empirical challenge, not unique to developing countries, is finding adequate methods to deal with confounding factors. Exposure to air pollution is likely correlated with various unobserved socio-economic dimensions, behavioral patterns, or other environmental factors that also affect health outcomes. Not accounting for such unobserved factors would bias the estimate of the impact of air pollution on health.

In this study, we overcome these data and empirical challenges to provide robust evidence quantifying the health impacts of short-term air pollution exposure from rural emissions in the context of a developing country. We use novel high-resolution satellite data on agricultural fires to generate plausibly exogenous variation in exposure to pollution across India. Like many other parts of the developing world, farmers in India widely use deliberate fires to burn vegetation and clear land to plant crops (Singh and Kaskaoutis, 2014).[3] During peak fire seasons in India, these agricultural fires can contribute to more than half of the particulate pollution load even within urban areas (Liu et al., 2018; Cusworth et al., 2018). It is also important to note that these agricultural fires are controlled burning activities limited to farmers' plots. Unlike wildfires or bushfires, these agricultural fires do not spread uncontrollably and are unlikely to cause damage to property or human life directly. Instead, air pollution from these fires is the primary mechanism through which they are likely to affect health.

We focus on identifying the effects of these fires on hypertension risk. High blood pressure is the leading risk factor for non-communicable disease mortality in both rich and developing countries (IHME, 2019). Medical and epidemiological studies have linked ambient air pollution to increased hypertension and cardiovascular stress (e.g., Hadley et al., 2018; Cosselman et al., 2015). This body of work has found that small pollution particles can enter the lungs' alveoli, which can trigger systemic inflammation and vasoconstriction, for example. These conditions can increase the risk of heart failure, arrhythmia, and cardiac arrest, among others. However, there are no prior studies that quantify, within a causal framework, the extent to which deliberate biomass burning events are detrimental to exposed individuals' cardiovascular health. One concern is that agricultural fires may be correlated with unobserved economic conditions that also influence health outcomes. We address this concern with daily data on wind direction, which we use to construct location-specific exposure measures to upwind and downwind fires.[4] The rationale for doing so is that upwind fires are likely to affect health purely through changes in pollution levels. We control for downwind fires in our empirical models, thereby capturing any local economic factors associated with fires. The combination of fire activity and wind direction provides a quasi-random source of variation in short-term air pollution exposure.[5]

We leverage data from various sources for this study. To measure fire activity, we use satellite data from NASA's Visible Infrared Imaging Radiometer Suite (VIIRS) Active Fire product (EOSDIS, 2016). With a pixel resolution of 375 m, we observe more than 1.2 million fire events during our sample period 2015 to 2016. Daily wind direction measures were obtained from the ERA-5 climate reanalysis data (Hersbach et al., 2020). These are all matched with data on blood pressure tests for nearly 784,000 individuals from the National Family and Health Survey (NFHS) – IV (IIPS and ICF, 2017).[6] In order to overcome the limitation posed by lack of ground monitoring data, we use satellite and model-derived pollution estimates from the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2; Gelaro et al., 2017), with a grid resolution of 0.625×0.5 degrees.[7] We observe daily location-specific pollution levels for fine particulate matter ($PM_{2.5}$) and its components: Black Carbon, Organic Carbon, SO_2, dust, and sea salt. Collectively, these data allow us to estimate micro-level reduced form regression specifications for the effects of upwind fires on hypertension risk and air pollution exposure.[8]

Our estimates suggest that, on average, a standard deviation increase in exposure to upwind fires increases the incidence of hypertension by 1.8%. Based on estimates of the value of statistical life (VSL) for India (Viscusi and Masterman, 2017), we find that these fires are associated with monetary costs of the order of $9 billion annually, due to hypertension-related additional mortality. We further show that upwind fires affect $PM_{2.5}$ concentrations, while downwind fires do not. We cannot rule out that other pollutants, also carried by wind and generated from biomass burning, may be partly driving our estimates on hypertension. Nevertheless, our results point to air pollution, collectively, being the primary mechanism through which the fires are affecting health outcomes.

[3] The widespread practice of stubble-burning may be partly attributed to intensification of cropping frequency. Given nonconvexities in net returns to farming, more intensive agricultural practices may have been adopted in response to the pressures from population growth and increased demand for food (Krautkraemer, 1994).

[4] A schematic for our definition of upwind fires is presented in Appendix Figure A.1.

[5] The empirical strategy that we use is similar in spirit to that used in recent studies to examine the impact of pollution from agricultural fires on birth outcomes in Brazil and the effect on test scores among students in China (Rangel and Vogl, 2019; Graff Zivin et al., 2020).

[6] The NFHS also collects data on blood hemoglobin levels (biomarkers for anemia) and glucose levels (biomarkers for diabetes). However, epidemiological literature suggests that these health outcomes are more likely to be affected by medium- or long-term pollution exposure (e.g., Honda et al., 2017; Lucht et al., 2018). We focus on hypertension, which has been more robustly linked to short-term exposure.

[7] This corresponds to a grid of approximately 50×50 km, depending on the location of the measurement.

[8] We estimate separate regressions for the effects of upwind fires on hypertension risk and air pollution. Following prior literature (Graff Zivin and Neidell, 2013), in this setting we caution against an instrumental variable approach directly linking air pollution and hypertension. The reason is that we do not observe all pollutants associated with the fires, such that the IV approach would violate the exclusion restriction. More details in Section 2.2.

Finally, we also look at heterogeneous effects of these fires by employing the Sorted Effects Method and Classification Analysis from Chernozhukov et al. (2018). This allows us to identify individual characteristics that are associated with vulnerability to air pollution. Results are well-aligned with epidemiological and medical literature. For example, we find that the estimated effects are significantly stronger for older males, smokers, individuals who were already on blood pressure medication, and individuals belonging to socially marginalized groups.

This paper contributes to a growing literature that aims to quantify the health impacts of air pollution. While previous studies have often focused on respiratory health as a key physiological mechanism through which air pollution risk is manifested, our results highlight the importance of examining hypertension as an additional pathway of impact. The impact of short-term air pollution exposure on hypertension may partly explain why previous studies find adverse effects also on labor productivity, cognition, mortality, and other crucial human capital outcomes (Zhang et al., 2018; Chang et al., 2016; Deryugina et al., 2019). Our findings speak to the potential impacts of other biomass fire events, such as large wildfires, to the extent that they similarly increase air pollution.[9] Our empirical approach could be adapted to examine the health impacts of exposure to air pollution in these settings as well.

2. Main effects of agricultural fires on hypertension risk

Fig. 1 illustrates the geographic variation in the survey locations of the individual blood pressure tests and three key variables of this study: fire activity; incidence of hypertension; and air pollution. We note that agricultural fires are particularly prevalent in the north-western, north-eastern, and eastern regions of the country. These are districts where farmers either use fire to clear their harvest residue on their fields between two cropping seasons or use land-clearing fires in districts where shift and burn agriculture is practiced (Singh and Kaskaoutis, 2014). Across the full sample, individuals are exposed to 2.8 upwind fires, on average, in the 24 h period leading to the day of the health tests. Considering only exposed individuals, the average number of upwind fires is closer to 9.6.

2.1. Main empirical specification and results

We implement reduced form regression analyses to formally examine the causal link between agricultural fire activity and cardiovascular distress. For identification of that link, we construct a variable that counts the number of "upwind fires" to which individuals in our sample are exposed. We count the number of fire pixels measured using the Visible Infrared Imaging Radiometer Suite (VIIRS) 375 m thermal anomalies and active fires data (EOSDIS, 2016) within a buffer of radius 50, 75, 100 or 150 km around each individual's location in our sample. Those fire counts are then classified as located upwind, downwind, or other directions, based on wind direction data from ERA-5 (Hersbach et al., 2020). This classification is presented in further detail in the schematic in Appendix Figure A.1. The exposure variable of interest is the number of upwind fires on the day before the blood pressure tests.[10] Our identification strategy thus relies on combining variations in wind directions and fire activity, generating plausibly exogenous variation in exposure to agricultural fires.[11]

Our regressions also incorporate district-by-month-of-sample fixed effects, to flexibly account for district and season-specific factors that vary across space. Effectively, our specifications compare blood pressure outcomes for individuals located within the same district and measured within the same month but exposed to different quantities of upwind fires on the day of the blood pressure test. On average, each month of the survey covers 33,000 individuals across 55 districts. The survey's roll-out determines the specific day within a district-month group on which an individual's blood pressure is measured. Therefore, the measurement date is unlikely to be correlated with any individual or household factors that affect health. This variation in the day of blood pressure measurement, combined with the plausibly exogenous variation in wind directions, allows us to estimate the causal effect of agricultural fire exposure on hypertension. In addition to the fixed effects, all of our specifications include: the number of fires in downwind and other (non up/down) directions; weather variables such as rainfall, temperature, wind direction, and wind speed; as well as a rich set of individual and household characteristics. These account for any local economic, agricultural or other factors which might be correlated with agricultural fires, pollution, and health outcomes. The exact regression specification is presented in Appendix B.1. Descriptive statistics for the outcomes and for the control variables are presented in Appendix Tables A.1 and A.2, respectively.

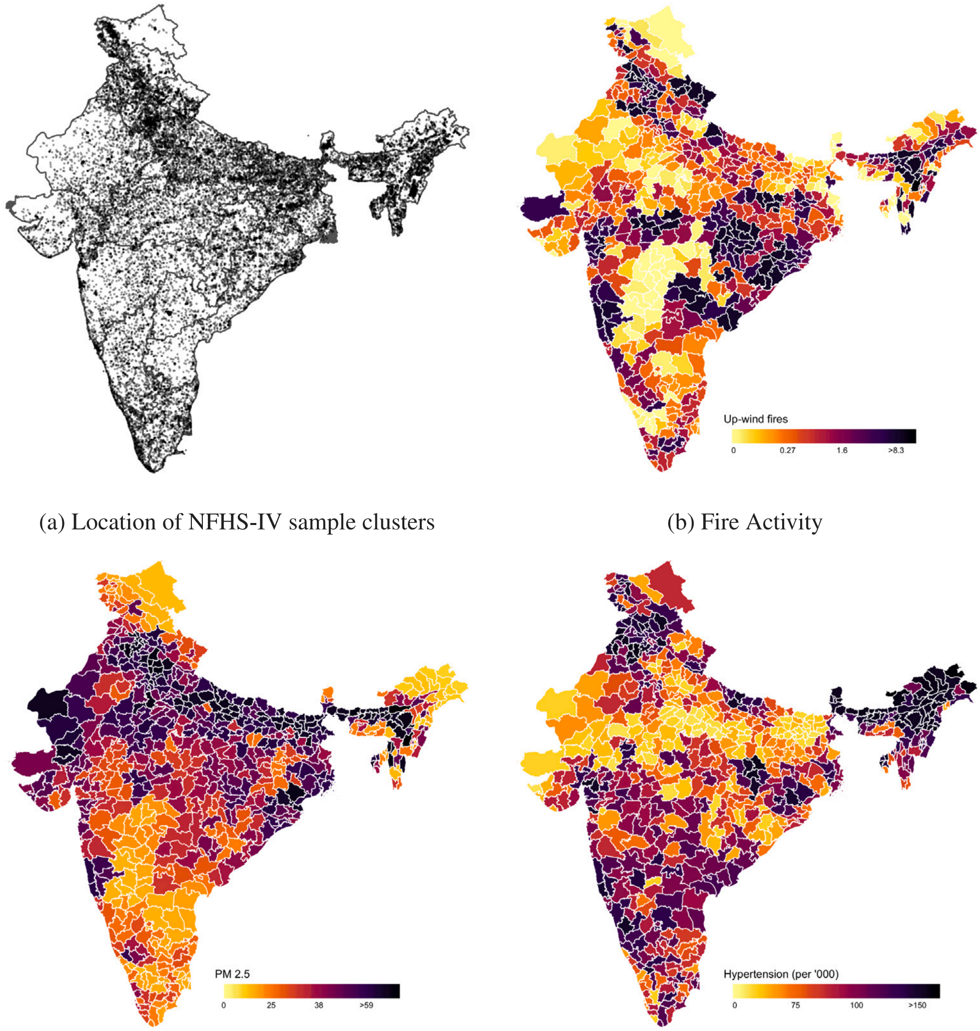
The main outcome of interest is a binary indicator variable for incidence of hypertension (i.e., systolic blood pressure $\geq$ 140 mmHg or diastolic blood pressure $\geq$ 90 mmHg).[12] We multiply this variable by one thousand, such that the coefficients can be

[9] Note, however, that different types of biomass burning events are significantly heterogeneous with regards to the pollutants that they generate, and how those are dispersed in the atmosphere (Andreae, 2019; Vicente et al., 2013).

[10] In Appendix C.4 we show that upwind fires from more than one day before the tests, or from days after the tests, do not significantly affect hypertension risk. We thus focus on the fires on the day immediately before the tests.

[11] We stress that our main source of quasi-exogenous variation are changes in wind directions, and not fire activity itself. In Appendix Figure C.4 we show that there is substantial day-to-day variation in wind directions during the NFHS survey period. In about 33% of the cases, wind direction quadrants on the interview day were different from those on the day before. This share is even higher (48%) if we define wind direction based on octants. The implication is that farmers are unlikely to be able to predict day-to-day changes in wind direction, thus have little scope to manipulate our main exposure variable (upwind fires).

[12] Systolic BP measures arterial pressure when the heart beats, while diastolic BP measures arterial pressure when the heart rests. We define hypertension based on the NFHS cutoffs for "Abnormal (Mildly Elevated)" blood pressure (IIPS and ICF, 2017). We focus on this binary outcome because clinical interventions are only recommended when BP crosses given thresholds (Messerli et al., 2007). An increase in BP, per se, does not pose a threat to health if BP still remains at normal levels.



(a) Location of NFHS-IV sample clusters (b) Fire Activity

(c) Air Pollution ($PM_{2.5}$) (d) Incidence of Hypertension

Fig. 1. Distribution of Sample Locations, Fire Activity, Air Pollution, and High Blood Pressure Incidence.
Notes: Panel (a) shows the sample locations (clusters) in the NFHS-IV survey data used in our study. Panel (b) shows the spatial distribution of the number of upwind fires in the 24 h leading to the day of the blood pressure test, averaged at the district-level. The measure is based on the number of fire pixels from the VIIRS data (EOSDIS, 2016) observed in a 75-kilometer radius surrounding the survey respondent's location. We classify fires as upwind using data on wind direction from ERA-5 climate reanalysis (Hersbach et al., 2020). "upwind" refers to the direction from which the wind is blowing relative to the location of interest (see Figure A.1). Panel (c) portrays the distribution of average $PM_{2.5}$ exposure at the district level on the day leading to the blood pressure test. The sample mean $PM_{2.5}$ exposure is 39.7 $\mu g/m^3$. Panel (d) shows the mean prevalence of hypertension (systolic blood pressure (BP)$\geq$ 140 mmHg or diastolic BP$\geq$ 90 mmHg) across districts. The sample mean hypertension incidence is 94.7 per ′000.

interpreted as marginal effects on incidence per thousand (′000).[13] Fig. 2 presents results from our main specifications. We find that upwind fires increase hypertension risk, while fires located downwind do not. Particularly, for a specification looking at fires within a 75 km radius, each upwind fire increases incidence of high blood pressure by 0.12 per thousand. For each standard deviation increase in upwind fires (approximately 14 fires), the incidence of high blood pressure increases 1.68 per thousand, representing

[13] Per thousand, or '000, is typically used in medical literature to measure the incidence of given health conditions, such as hypertension. It represents how many people, out of one thousand, suffer from the condition. This is a normalized measure, much like percentages, which allows us to compare incidence across samples or over time.

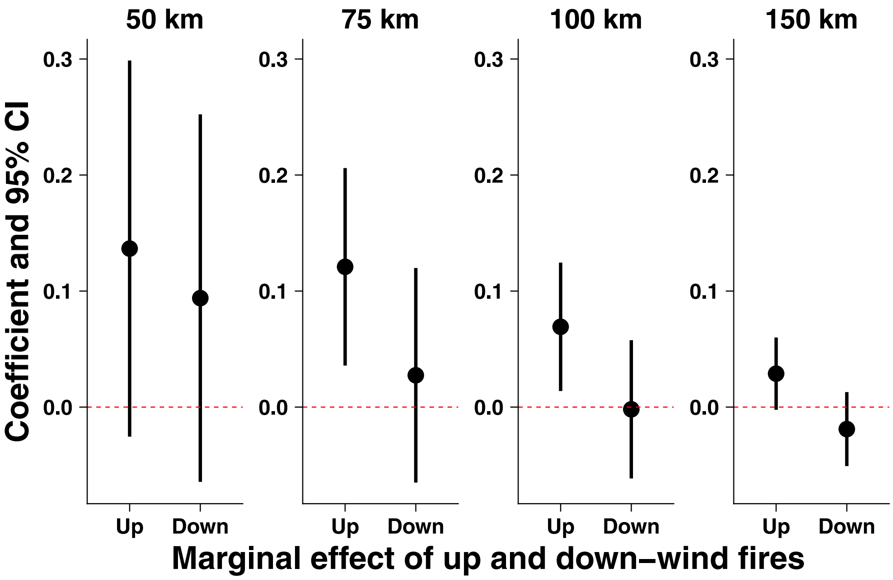


Fig. 2. Impact of exposure to fires on the incidence of hypertension.
Notes: The figure shows the marginal effect of exposure to one additional fire on the day leading to the blood pressure (BP) test on the risk of hypertension. Coefficients and associated 95% confidence intervals are shown from separate regressions in each column using 50, 75, 100, and 150 km radius buffers for fire counts, respectively. The dependent variable is a binary variable for the incidence of hypertension which takes the value 1000 if the average of three BP tests shows systolic BP ≥ 140 mmHg or diastolic BP≥ 90 mmHg, and zero otherwise. Up and down-wind fires classification is based on 90-degree wind sectors. All specifications include district-by-month of sample and day of week fixed effects, controls for weather, and demographic and household characteristics.

about 1.8% of the average incidence for individuals that were not exposed. Fig. 2 also shows that results remain similar with alternative radii.[14] Regression estimates corresponding to Fig. 2 are presented in Appendix Table C.1.

Our estimates remain robust across a variety of model specifications and robustness checks. We obtain similar results using a logit estimation (Appendix Table C.2).[15] In Appendix Table C.3 we show that the above results hold with a specification that does not include weather or demographic controls, suggesting that the district-by-month-of-sample fixed effects may already capture most of the confounding variation in this context. The effects that we find are also robust to using more demanding sets of fixed effects. In Appendix Table C.4 we see that the coefficient on upwind fires remains qualitatively similar as we progressively change the fixed effects from district-by-month-of-sample to NFHS sample cluster-by-week-of-sample.[16] Results are also statistically significant with an alternative definition of hypertension risk, as shown in Table C.5. Although, in that case, the magnitudes of the effects seem smaller compared to the sample average incidence of hypertension. Table C.6 shows that results hold if we classify upwind and downwind fires based on 45-degree octants (rather than 90-degree quadrants used in the main specification).

Finally, in Appendix C.5 we consider variants of our main specification with continuous blood pressure measures (systolic and diastolic) as the outcomes. Results are shown in Appendix Figure C.2. We show that the coefficients on downwind fires are null across all specifications. Conversely, we find positive and statistically significant effects for upwind fires, but only for subsamples of "high risk" individuals who had systolic BP ≥ 120; diastolic BP ≥ 80. Additionally, heterogeneity analyses in Appendix Figure C.3 suggest stronger effects for individuals with body-mass index (BMI) ≥ 30, or with age ≥ 40.[17] Collectively, these results suggest

[14] As one would expect, increasing the distance used to measure exposure results in smaller marginal effects on blood pressure. This reduction in impact is consistent with the air quality effect of fires reducing with distance. Conversely, shorter distances limit the available variation in the number of fires we detect in our data, leading to a loss of precision. We also run into the issue of measurement error in the individual's location with shorter distances – the geocoordinates of the sample cluster locations in the NFHS data are randomly displaced by up to 10-kilometers in rural areas for preserving the privacy of respondents (Burgert et al., 2013). Finally, the climate reanalysis data that we use is too coarse to calculate reliably define up and down-wind directions at smaller distances increasing the potential for misclassifying up and down-wind fires. Therefore, we focus on the results using a 75-kilometer radius buffer in our main discussion.

[15] Our findings are consistent with those from prior studies in similar settings. When converted to odds ratios, our estimates suggest that a one s.d. increase in upwind fire exposure (about 14 fires) increases the odds of hypertension risk by 1.02. Recent estimates from California suggest that one day of wildfire smoke exposure increases the relative risk of emergency department visits for hypertension by between 1.01 to 1.08 for light, medium, and dense smoke, respectively (Wettstein et al., 2018). Similarly, Singh et al. (2021) find that high intensity biomass burning events are associated with odd ratios ranging from 1.003 to 1.32, for hypertension among populations in four North Indian states.

[16] NFHS sample clusters are survey enumeration areas roughly corresponding to a village in rural areas. This is the lowest level at which geographic location information is available in the NFHS.

[17] Coefficients from Appendix Figure C.3 were obtained from the interactions of upwind fires with given categorical variables of interest.

that agricultural fire-induced hypertension risk may be particularly prevalent for a subset of vulnerable individuals. Estimates of average effects across a broad sample may mask this risk. In Section 3 we perform a deeper analysis of heterogeneity, to provide further insight about risk factors.

2.2. Air pollution as the mechanism linking fire activity and cardiovascular distress

Based on medical and epidemiological literature,[18] we argue that fire activity increases hypertension risk primarily through increased air pollution. To support this argument, we provide evidence within our study setting that increased fire activity indeed leads to higher pollution concentrations. We use regression specifications similar to those described in Section 2.1, but with measures of air pollution as the dependent variables. In particular, we focus on fine particulate matter ($PM_{2.5}$) concentrations. We construct daily average $PM_{2.5}$ measures for each NFHS cluster location (i.e., village) using climate reanalysis data from MERRA-2 (Gelaro et al., 2017).[19] Additionally, we run separate regressions for sulfate (SO_2), organic carbon (OC), black carbon (BC), dust, and sea-salt, which are all components of our $PM_{2.5}$ measure.

Results in Fig. 3 and Appendix Table D.1 show that upwind fires within 75 km surrounding NFHS respondents' locations significantly increase air pollution concentrations. Consistent with wind transporting pollution from fires, we see that upwind fires have a relatively larger effect compared to downwind fires on Black Carbon, Organic Carbon, and SO_2 – all of which are pollutants commonly associated with biomass fires (Akagi et al., 2011). Dust and sea-salt particulate concentrations, on the other hand, are determined by long-range atmospheric transport and proximity to arid or desert regions and are less likely to be affected by fires. Consequently, we see that the impacts of fires on dust and sea salt particulate matter are close to zero. Conversely, the effects on the combined $PM_{2.5}$ are substantial. We find that a standard deviation increase of exposure to upwind fires increases total $PM_{2.5}$ by about 27%, relative to the unexposed group average of 38.6 $\mu g/m^3$.

The above results use modeled pollution measures from satellite data and atmospheric chemical transport estimates. We find very similar estimates using the limited amount of monitoring station data available in India for the sample period (Appendix Figure D.1). In Appendix Table D.2 and Figure D.2, we see that a standard deviation increase in upwind fires increases $PM_{2.5}$ measured at monitors by 26%, relative to the mean $PM_{2.5}$ of 83.8 $\mu g/m^3$ on monitor-days with zero upwind fire – a magnitude very similar to what we find using modeled $PM_{2.5}$ data across the NFHS sample locations. Additionally, we also find that fires affect multiple pollutants simultaneously with upwind fires increasing PM_{10}, NO, and NO_2 concentrations.

The significant associations shown in Fig. 3 may lead one to consider using upwind fires as an instrumental variable (IV) to estimate the direct effect of particulate matter exposure on hypertension risk. In Appendix E we present results from one such approach. However, we refrain from interpreting those results as causal, and we caution against an IV strategy in settings similar to ours, for two main reasons. First, evidence from the atmospheric science literature shows that biomass burning events are associated not only with $PM_{2.5}$ emissions, but also with emissions of carbon monoxide, nitrogen oxides, volatile organic compounds (VOCs), and ozone, among others (Andreae, 2019; Vicente et al., 2013). Second, epidemiological studies suggest that these other pollutants may also be associated with hypertension risk (for reviews, see: Yang et al., 2018; Orellano et al., 2020). The implication is that upwind fires are not a valid instrument for $PM_{2.5}$, due to violations of the "exclusion restriction", and to the extent that wind also carries other pollutants.[20]

In that case, it is challenging to identify which pollutants are more strongly associated with hypertension risk. This is particularly true in developing country settings, where reliable measurements and comprehensive measures of air pollution are scarce (World Bank, 2022). In Appendix E we show that, for our setting, two-stage least squares (2SLS) estimates of the effects of $PM_{2.5}$ on hypertension risk are sensitive to violations of the exclusion restriction. We perform simulations based on Conley et al. (2012), to adjust the 2SLS confidence intervals, assuming that other pollutants also affect hypertension. Results suggest that the 2SLS estimates are no longer consistent if there exists another pollutant with at least one third of the emissions factor of $PM_{2.5}$, and which similarly causes at least one third of the health damages.

We stress that this does not imply that air pollution, as an ensemble of pollutants, may not be the main mechanism through which upwind agricultural fires affect hypertension. Recall that our main specifications in Section 2.1 control for fires in other wind directions, which we find to be associated with null and non-significant coefficients. The implication is that whatever is causing an increase in hypertension risk must be carried, by wind, from the locations where the fires are happening, in direction to the surveyed villages. The natural conclusion is that air pollution is the primary mechanism in this context.

[18] Among others, see: Al-Kindi et al., 2020; Sanidas et al., 2017; Cosselman et al., 2015; Mills et al., 2009; Prabhakaran et al., 2020.

[19] We use the MERRA-2 hourly estimates for surface concentrations of sulfate, organic carbon, black carbon, dust and sea-salt particulate matter with a diameter of less than 2.5 μm. We combine these species level estimates to obtain total $PM_{2.5}$ concentrations using ground-validated conversion factors from He et al. (2019). We aggregate the hourly estimates to 24-hourly averages for use in the analysis.

[20] Our arguments are in line with Graff Zivin and Neidell (2013), who stress the complexity of identifying the effects of multiple pollutants in these types of settings. Rather, they recommend estimating reduced form specifications linking the outcomes of interest directly to the source of pollution (i.e., agricultural fires).

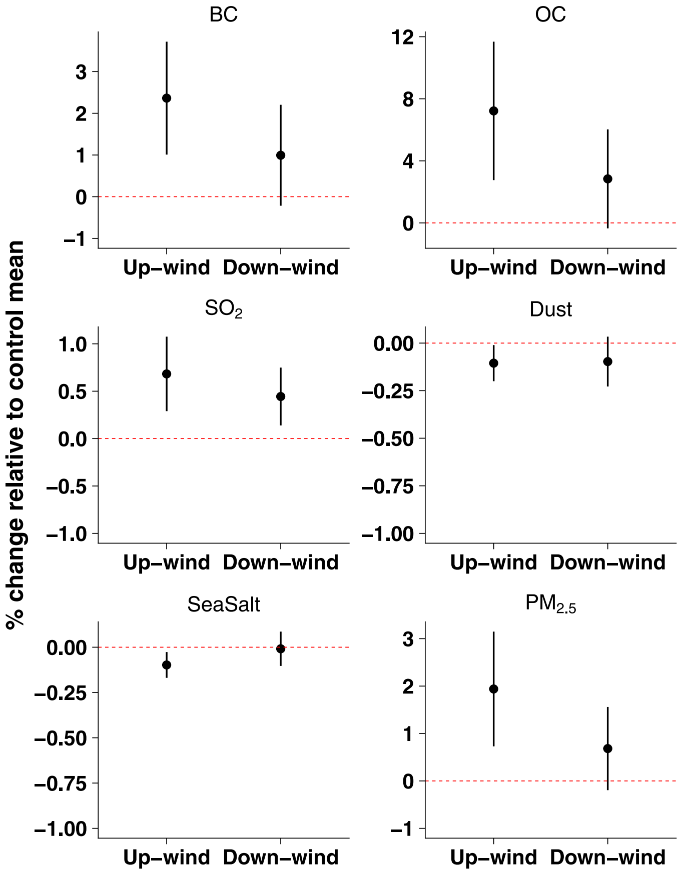


Fig. 3. Effects of agricultural fires on local air pollution.
Notes: Plots show the marginal effects of up- and downwind agricultural fires in a 75-kilometer radius surrounding the survey respondent's location on air pollution concentrations measured using data from atmospheric chemistry transport models (MERRA-2). Coefficients are transformed to show the percentage change relative to the sample mean of the outcome variable along with the associated 95% confidence intervals. Each figure shows estimates from a separate regression for Black Carbon (BC), Organic Carbon (OC), Sulphur dioxide (SO_2), Dust , and Sea Salt particulate matter. We combine these species-level estimates to obtain total $PM_{2.5}$ concentrations using ground-validated conversion factors from He et al. (2019). The effect on $PM_{2.5}$ is shown in the last panel. Up- and downwind is based on 90-degree wind sectors. All specifications control for rainfall, temperature, wind speed, and include district-by-month of sample and day of week fixed effects.

3. Heterogeneity and characteristics of most affected individuals

To identify the heterogeneity of the effects of agricultural fires across individuals in our sample, we implement the Sorted Effects Method (SEM) and Classification Analysis (CA) (Chernozhukov et al., 2018). SEM consists of rerunning the analysis from Section 2.1 but at multiple quantiles of the available data (further details in Appendix B.2). Specifically, we implement the SEM for a binary response model (predicting the incidence of hypertension), a continuous independent variable of interest (number of upwind fires), plus the controls described in Section 2. With SEM, we identify the partial effect of the upwind fires, holding all other factors constant.

Fig. 4 presents the main results from the SEM, where we rank the estimated partial effects from lowest to highest. This ranking identifies portions of the sample distribution likely to be least or most affected by the fires. The estimates reveal significant heterogeneity across the sample. The least affected group (bottom 10th percentile) experience increases of high blood pressure incidence of 0.02 per thousand for exposure to each additional upwind fire. On the other hand, in the most affected group, the effects can be as large as 0.29 per thousand (almost fifteen times larger). Once the least and most affected groups are identified, it is possible to compare their characteristics with a Classification Analysis (CA; further details presented in Appendix B.2).

Table 1 presents results from the Classification Analysis. We calculate averages for key variables of interest across groups identified as least and most affected by upwind fires. We then take the differences in averages. Bootstrap-based inference techniques are used to test for statistically significant differences in these characteristics across the two groups. We find that variation in upwind fire's impact along individual physiological and behavioral characteristics is consistent with known risk factors for hypertension from the medical literature. For instance, we see that 18.3% of the most affected individuals already held prescriptions for blood pressure medication. Also, 5% of them were smokers. Virtually no individuals from the least affected group were smokers or reported having

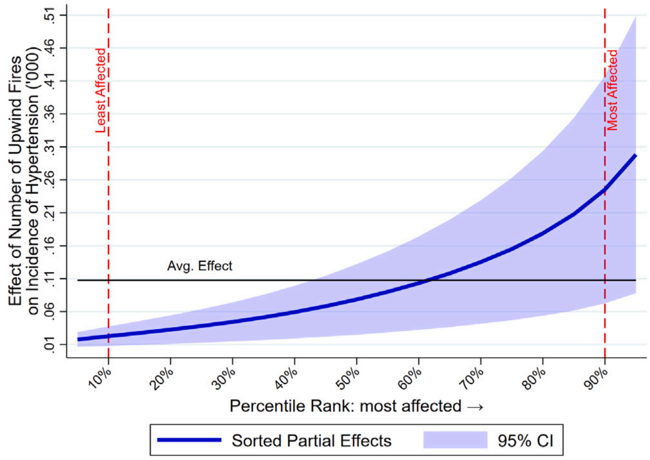


Fig. 4. Results from the Sorted Effects Method.
Notes: This figure presents the results from the Sorted Effects Method (Chernozhukov et al., 2018). The blue line represents the partial effects of upwind fires on incidence of high blood pressure, holding all other factors constant. The blue shaded area represents 95% confidence intervals. The vertical red dashed lines represent the cutoffs for the most (top 10%) and least (bottom 10%) affected individuals. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Results from the Classification Analysis.

	(1) Most affected	(2) Least affected	(1) - (2) Difference
Prescription for BP (yes=1)	0.1835	0.0000	0.1835
	(0.0018)	(0.0001)	(0.0018)
Smoker (yes=1)	0.0499	0.0014	0.0485
	(0.0016)	(0.0002)	(0.0018)
Male (yes=1)	0.2974	0.0250	0.2723
	(0.0029)	(0.0014)	(0.0036)
Scheduled tribe (yes=1)	0.2167	0.0890	0.1277
	(0.0026)	(0.0037)	(0.0056)
Age	43.0620	18.6394	24.4225
	(0.0480)	(0.0576)	(0.0793)
Clean cooking fuel (yes=1)	0.5147	0.3105	0.2042
	(0.0036)	(0.0063)	(0.0086)
Richest households (yes=1)	0.2613	0.1598	0.1015
	(0.0032)	(0.0036)	(0.0058)
BMI	26.5612	18.4224	8.1388
	(0.0329)	(0.0275)	(0.0495)
Outdoor cooking (yes=1)	0.7763	0.6228	0.1534
	(0.0030)	(0.0056)	(0.0083)
Rural households (yes=1)	0.6389	0.7379	−0.0990
	(0.0040)	(0.0043)	(0.0082)
Scheduled caste (yes=1)	0.1485	0.2078	−0.0594
	(0.0026)	(0.0043)	(0.0068)
Years of education	5.7859	8.9379	−3.1521
	(0.0374)	(0.0450)	(0.0680)
Poorest households (yes=1)	0.1061	0.2098	−0.1037
	(0.0021)	(0.0054)	(0.0068)

Notes: This table summarizes the results from the Classification Analysis. We present average characteristics of the individuals who were most and least affected by upwind fires. The two groups were defined based on the top and bottom 10% cutoffs shown in Fig. 4. The last column shows the difference in averages between the two groups. The rows are sorted from highest to lowest percentage differences. Standard errors, in parentheses, were obtained with the bootstrap inference procedure from Chernozhukov et al. (2018). All differences are statistically significant at 1%, even after accounting for multiple hypotheses testing.

blood pressure prescriptions. As expected, age and BMI are important signals of vulnerabilities. Most affected individuals are, on average, 43 years old, while the least affected are younger than 19. The average BMI of most affected individuals is 26.5, above the “overweight” cutoff (WHO, 2004). Conversely, the average BMI of the least affected individuals is 18.4, closer to normal ranges.

Our analysis also reveals significant heterogeneity in the impact of fires on hypertension across gender. Almost 30% of the most affected individuals were male, compared to only 2.5% of the least affected group (here we note that our total sample consists of 24% males). Differences in biological mechanisms across gender, resulting in a higher risk of hypertension among men (Song et al., 2020), may be partly responsible for this gender differential. Additionally, in the study setting, men may also be more likely to be exposed to pollution from agricultural fires due to differences in gender roles and occupational structure. In Indian rural communities, men often work in agriculture or other outdoor activities, while women traditionally focus on in-home activities. We also see that social marginalization is another critical dimension that can exacerbate air pollution's health impacts. Our heterogeneity results suggest that the most affected individuals have a higher likelihood of belonging to Scheduled Tribes – a group that was historically marginalized.

We see a decline in the risk of hypertension due to air pollution with improved education levels. Most affected individuals are typically less educated (with an average of 5.8 years), even though they are older. This variation may partly reflect advances in the Indian education system and living standards, where younger generations attain more schooling and are less likely to work in agriculture. It could also be that more educated individuals engage in defensive behaviors, such as wearing masks or staying indoors during high pollution events. However, our results suggest that even though some households may be able to invest in technologies to improve the air quality within their homes, they cannot fully mitigate the detrimental health effects of ambient air pollution. For instance, we find that individuals with higher risk are more likely to belong to households that cook outdoors and are more likely to use clean cooking fuels, which would reduce indoor air pollution levels. We also see that the most affected individuals are likely to belong to wealthier households. These results highlight the importance of addressing outdoor air pollution in this setting.

4. Conclusion

We provide causal estimates of the extent to which agricultural fires increase hypertension risk. Our empirical strategy combines micro-level data on fire activity and wind directions to generate quasi-random variation in air pollution exposure. Our results show that a standard deviation increase of exposure to upwind fires increases the incidence of hypertension by 1.8% – relative to the average hypertension incidence among individuals not exposed to upwind fires. With a heterogeneity analysis, we also show that the effects can be significantly larger for more vulnerable individuals. For example, we find that older males, smokers, individuals on blood pressure medication, and individuals belonging to socially marginalized groups are significantly more vulnerable.

Using the nationally representative nature of our data, we estimate that the exposure to fires contributes to nearly 14% of total mortality due to hypertension in India annually. Using value of statistical life estimates, we find that the additional mortality imposes a substantial monetary cost of USD 9 billion each year (2.29 billion lower bound, 18.24 billion upper bound).[21]

The large health burden posed by fires reflects the fact that agricultural fires are a major contributor to overall pollution in India. Overall, agricultural fires are estimated to contribute to nearly a quarter of all black carbon, organic carbon, and carbon monoxide emissions in India (Venkataraman et al., 2006). In peak seasons, fire can contribute to nearly half of particulate pollution even in urban areas such as the capital city of Delhi (Liu et al., 2018). We also find that exposure to fires is widespread. Within our sample, nearly a third of respondents were exposed to at least one fire in the day before BP tests and, on average, experienced almost 38 days with upwind fires within a year. Finally, overall ambient air pollution is estimated to be the leading reason accounting for 22%–53% of all deaths from cardiovascular diseases (Nair et al., 2021).

While previous studies have often focused on respiratory health as a key physiological mechanism through which air pollution risk is manifested, our results highlight the importance of examining hypertension as an additional pathway of impact. The impact of short-term air pollution exposure on hypertension may explain why previous studies find adverse effects also on labor productivity, cognition, mortality and other important human capital outcomes (Zhang et al., 2018; Chang et al., 2016; Deryugina et al., 2019). Our findings also speak to the potential adverse health impacts of other biomass fire events, such as large wildfires, which are also prevalent in some developed economies.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2022.102723.

[21] Details of these calculations are presented in Table B.1.

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