



## Crop Fires and Cardiovascular Health – A Study from North India

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### ABSTRACT

We examine the impact of exposure to biomass burning events (primarily crop burning) on the prevalence of hypertension in four North Indian states. We use data from the National Family Health Survey-IV for 2015-16 and employ a multivariate logistic and linear model to estimate the effect of exposure to biomass burning on the prevalence of hypertension and blood pressure, respectively. The adjusted odds ratio of hypertension among individuals living in areas with high intensity of biomass (HIB) burning (defined as exposure to > 100 fire-events during the past 30 days) is 1.15 [95% CI: 1.003–1.32]. The odds ratios further increase at a higher intensity of biomass burning and downwind fires are found to be responsible for the negative effect of fires on cardiovascular health. We also find that the systolic and diastolic blood pressure for older cohorts is significantly higher due to exposure to HIB. We estimate that elimination of HIB would prevent loss of 70–91 thousand DALYs every year and 1.73 to 2.24 Billion USD (in PPP terms) over 5 years by reducing the prevalence of hypertension. Therefore, curbing biomass burning will be associated with significant health and economic benefits in North India.

### 1. Introduction

Cardiovascular diseases are one of the leading non-communicable diseases in the world (Roth et al., 2018). In India, cardiovascular diseases contribute to 28.1% of the total deaths and 14.1% of the total disability-adjusted life years (DALYs) in 2016 with high systolic blood pressure and air pollution being identified as important leading overlapping risk factors (Prabhakaran et al., 2018). Studies have shown that exposure to air pollution increases systolic and diastolic blood pressures (Liang et al., 2014), incident hypertension (Chen et al., 2014; Huang et al., 2019; Xie et al., 2018) and adverse cardiovascular outcomes including mortality (Pope III et al., 2004; Rajagopalan et al., 2018), but such evidence is lacking in India.

A major source of air pollution in developing countries is agricultural biomass burning and forest fires. Biomass burning is an agricultural practice of burning crop residues to prepare the land for the next seasonal crop. The problem has become more prevalent with the mechanization of harvesting, which leaves crop residue on the fields. The crop residue (stubble) is burned by farmers which is an easy option to clear

the land. India is the third-largest emitter of carbon emissions associated with crop burning after China and the United States of America (FAO, 2017).

Rice and wheat crop stubble burning are the major contributors to crop burning in India (Jain et al., 2014). The stubble burning practice is seasonal in nature and corresponds to the harvest seasons for these crops. The two main seasons are kharif crop harvest (rice stubble burning) which takes place in the months of October and November (it spills over to the month of December in some states as well); and rabi crop harvest (wheat straw burning) which happens in the months of April and May (Vadrevu et al., 2011). Punjab and Haryana are agriculturally very productive states and crop burning is conducted routinely during the harvest seasons. Studies have established that the extent of stubble burning is particularly high in the Indo Gangetic Plains (Venkataraman et al., 2006) which comprises of North Indian States of Punjab, Haryana, Uttar Pradesh and Bihar. Another source of biomass burning are forest fires, where a piece of land is cleared for human use. This practice is mostly prevalent in North Eastern states while states in Indo-Gangetic Plains have very few forest fire incidents (see [Appendix Figure A1 and](#)

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A2 for seasonality of fire-events and composition of fires in North Indian states). For years 2015-16, 96% of biomass burning events which were detected in the states of Punjab, Haryana, Uttar Pradesh and Bihar were crop fires.

The issue is compounded by local geographic and prevalent atmospheric conditions which particularly worsen air pollution. Studies have shown that aerosols released in Punjab and Haryana due to crop residue burning spread to the western and central Indo-Gangetic Plain (IGP) resulting in seasonal smog in these regions (Bikkina et al., 2019; Chowdhury et al., 2019; Kaskaoutis et al., 2014). The recent Global Disease Burden (GDB) study for India (Pandey et al., 2020) estimated the economic loss due to premature deaths and morbidity attributable to outdoor particulate matter pollution and in each of the 4 North Indian states in our study (Punjab, Haryana, Uttar Pradesh and Bihar) more than 0.9% of the GDP was lost due to exposure to ambient air pollution. The Government of India has banned crop burning in the past (2015) and also launched a program in 2018 to curb crop burning during the peak pollution season (MoAFW, 2019), but still, this practice is quite prevalent, especially in Northern India. Outreach to the farmers with evidence of health impacts of biomass burning has been put forward as one of the key drivers in resolving this environmental problem.

In the present study, we examine the association between exposure to pollution enhancing activity of crop burning (biomass burning) and hypertension in a large population of North India by using a cross-sectional survey and correlating it with high-resolution satellite data of fire events. We also estimate the economic implications of biomass burning impact on DALYs due to its impact on increased chances of hypertension in the exposed population.

## 2. Study population and sample

We have used data from the latest round of the National Family Health Survey (NFHS-IV) for India for 2015-16. The survey for the four North Indian states was conducted in the months of January 2015 to September 2016. The NFHS-IV followed a multi-stage random sampling design. First, the sampling frames were developed based on non-overlapping units of geography, which were identified as the primary sampling units (PSUs), by states and urban and rural areas within each state, and then a fixed proportion of households were selected using systematic random sampling within each PSU (alternatively referred to as clusters). The NFHS-IV recorded GPS coordinates of the sampled clusters which we use in our analysis. To ensure respondent confidentiality the GPS locations of the clusters were displaced (by NFHS) randomly by 5 km for rural clusters and by 2 km for urban clusters. NFHS also reported random displacement of some of the clusters by as much as 10 km.

The NFHS-IV provides systolic blood pressure (SBP) and diastolic blood pressure (DBP) at the national, state and district level in a representative population of women aged 15–49 years and men aged 15–54 years. Automated blood pressure (BP) apparatus (Omron HEM-8712) was used to record three BP readings for each individual. BP was recorded in the left upper arm, with at least 5 min interval between each measurement and a 5 min of quiet sitting before the first measurement.

Our study uses data collected for 211,152 individuals from four North-Indian states - Punjab, Haryana, Uttar Pradesh and Bihar (Fig. 1). We have excluded individuals for whom all three readings were not available. We also excluded individuals on anti-hypertensives, pregnant females and individuals with missing information and BP values below SBP < 80 mm Hg and DBP < 50 mm Hg, which were considered below physiological levels and erroneous recordings. We were able to obtain a complete data set including BP readings, demographic variables, exposure variable (i.e. fire-events) and weather-related factors (temperature

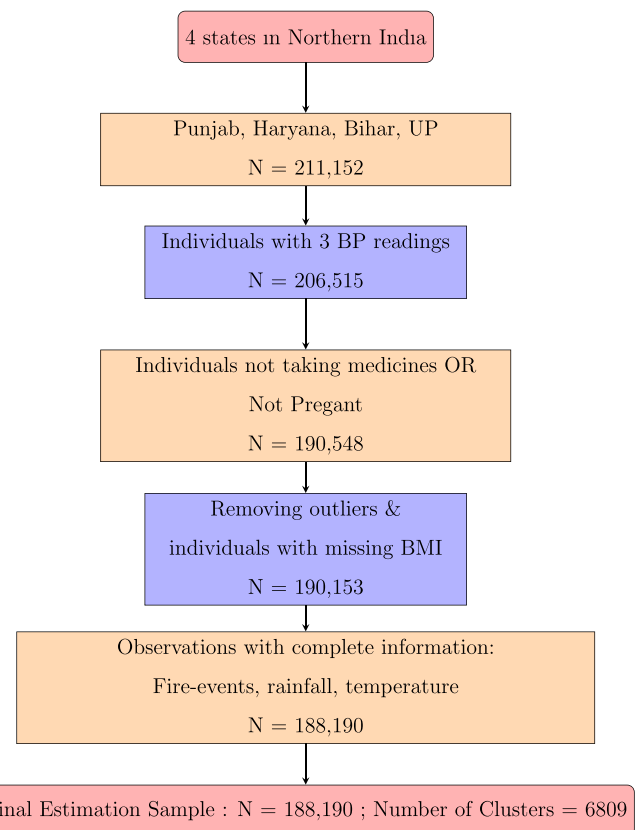


Fig. 1. Schematic representation of individuals included in the study (UP: Uttar Pradesh; BP: blood pressure; BMI: body mass index).

and rainfall) for 188,190 individuals from 6809 clusters, which we used for our final analysis (188,190 out of 211,152; 89.12% of the sampled population; Fig. 1).

## 3. Outcome variables

### 3.1. Hypertension

Data on SBP and DBP were obtained from NFHS-IV. We diagnosed hypertension as SBP  $\geq$  140 mm Hg and/or DBP  $\geq$  90 mm Hg as per the ESH/ESC 2018 guideline; (Mancia et al., 2013; Williams et al., 2018). We disregarded the first BP measurement and used the mean of the second and third reading as the individual's BP which has been shown previously to be the most accurate assessment of blood pressure (Jose et al., 2019). The final measure is a dichotomous variable which takes value 1 if SBP or DBP are above the cut-offs defined above and takes value 0 otherwise.

### 3.2. Systolic and diastolic blood pressure

Continuous variables for blood pressure were also analyzed separately. These continuous variables include blood pressure readings for systolic blood pressure (SBP) and diastolic blood pressure (DBP).

### 4. Exposure variable

The GPS locations of the clusters (PSUs) are combined with satellite data on biomass burning events from Fire Information for Resource Management System (FIRMS) provided by the National Aeronautical

Space Agency (NASA) that captures real-time active fire locations across the globe. The FIRMS provides Moderate Resolution Imaging Spectroradiometer (MODIS) data that records fire incidents in the form of pixels with each pixel being identified by a latitude and longitude tag. Each such pixel represents an area of one square kilometre (1 km X 1 km in size). The MODIS data has been available daily since March 2000 and NASA reports that the fires captured by this dataset are mostly vegetation fires. NASA data on biomass burning events (fire-events) also provides a confidence variable, which depicts the probability of occurrence of the fire event and it ranges from 0 to 100 (Giglio et al., 2016).

We used the confidence variable to construct a probability-weighted count of fire-events (Rangel & Vogl, 2019) around the cluster location (100 km radius) for last 30 days from the date of NFHS-IV interview of the individual. The fire-count variable was constructed in the following way: the total number of probability-weighted fire-events was calculated in the 100 km radius around the cluster location, from this probability-weighted total count of fire-events in 10 km radius was subtracted. The fire count from the inner circle (of 10 km radius) was subtracted to account for the uncertainty of true cluster location due to displacement (Fig. 2). Based on these calculations, we first show broad regional patterns in fire burning activity in our data. Fig. 2 shows a district-wise distribution of the mean number of fire-events (mean is calculated as an average of exposure to fire-events for all individuals residing in a district). The districts in the Bihar had a much lower incidence of fire-events (less than 30) as depicted by lighter shade. As we moved westward, Punjab and Haryana had a much higher incidence of these events (with many districts experiencing more than 100 fire-events) as depicted by the darker shades.

However, within a district, individuals can have a different level of exposure to biomass burning. Therefore, using the cluster location in which an individual resides, we calculated the number of fire-events in its 100 km radius in the past 30 days from the date of the interview. Our key exposure variable is a dichotomous variable - high-intensity biomass burning (HIB) which takes value 1 if an individual experiences an exposure to  $\geq 100$  fire events in an area of 100 km radius around the cluster during the past 30 days from the date of the interview, and 0 otherwise.

The violin plot (Fig. 3) shows the distribution of this calculated number of fire-events for all the individuals in our study. The mean number of fire-events was 47.1 and 9.8% percent of the surveyed individuals were exposed to HIB during the past 30 days from the date of the interview. We observe that no individuals from Bihar experienced exposure to high intensity biomass burning and there are many individuals from the other three states (Punjab, Haryana and Uttar Pradesh) who did not get exposed to high intensity biomass burning, together these individuals serve as a control group in our analysis since they experience low intensity exposure to biomass burning (HIB = 0).

## 5. Covariates

### 5.1. Demographic and other controls

We also use data on various risk factors (available from NFHS-IV dataset) which are associated with hypertension these include - dummy variables for eight age groups (15–19, 20–24, 25–29, 30–34, 35–39, 40–44, 45–49 and 50–54), dichotomous control for gender, indicator variable for alcohol consumption, indicator variable for smoking behaviour, body mass index (BMI), level of education (dummy variable for education level primary education or above), use of clean cooking fuel in the household (dichotomous control for usage of liquefied petroleum gas or electric stoves for cooking), economic status captured by five classes of wealth index and place of residence (rural or urban).

### 5.2. Meteorological variables

We additionally used rainfall and temperature data from ERA-

Interim dataset to account for local weather conditions. ERA-Interim data is produced by a data assimilation system that includes a 4-dimensional variation analysis with a 12-h analysis window. The spatial resolution of the dataset is approximately 80 km (T255 spectral) on 60 levels from the surface up to 0.1 hPa. More details are provided in ERA Interim Report, ECMWF, 2016. We analyzed the data available at the lowest level. Average rainfall and temperature were estimated in the 100 km radius around the cluster location for each individual using gridded data interpolated in a GIS platform.

We also use wind direction in our analysis.<sup>1</sup> Wind direction is expected to play an important role in modulating the outflow of fire burning residues emitted from a fire event. To account for this, we tag each fire event (using its geo location) with wind direction using monthly wind direction data. We use ERA-Interim data of  $u$  (zonal wind) and  $v$  (meridional wind) at 10 m from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-Interim dataset at  $0.125^\circ \times 0.125^\circ$  resolution.

The wind direction was estimated as in equation (2) (Chowdhury et al., 2017):

$$\text{winddirection} = [\text{atan}(u/v) * (180/\pi)] + 180 \quad (1)$$

The wind direction is coded in degrees, such that 0 corresponds to wind from due North, and 180 corresponds to wind from due South. For our analysis, using the wind direction at a fire-event, we construct a  $45^\circ$  modal octant around this wind direction which captures the pollution dispersion from polluting source that is fire-events in our case. If a cluster falls in this modal octant then this fire-event is tagged as a downwind fire-event for that cluster (fires occurring in opposite octant are tagged as upwind fire-events). Downwind fire-events are likely to affect local pollution levels.

## 6. Models

We used multivariate logistic regression to study the association between hypertension with high intensity biomass burning (HIB). We look at individual  $i$ , from cluster  $c$ , belonging to a district  $d$ , surveyed in month  $m$  and year  $t$  and run a multivariate logistic model:

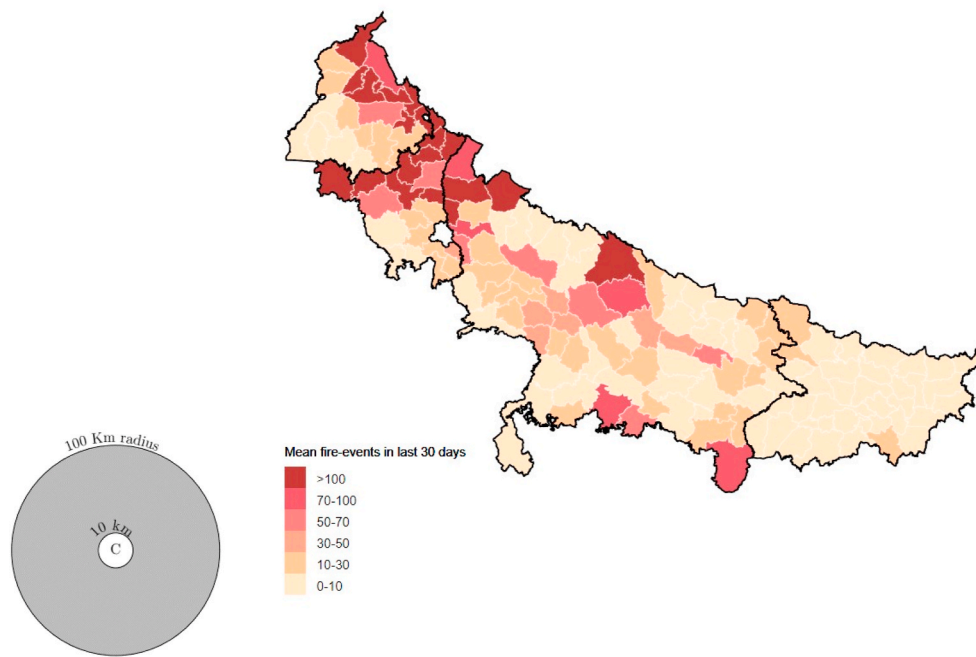
$$\text{Pr}(Y = 1 | \text{HIB}, X) = G(\alpha + \beta \text{HIB}_{icdmt} + \theta X_{icdmt} + \rho_d + \sigma_m + \varphi_t) \quad (2)$$

where  $G$  is the cumulative density function of logistic distribution.

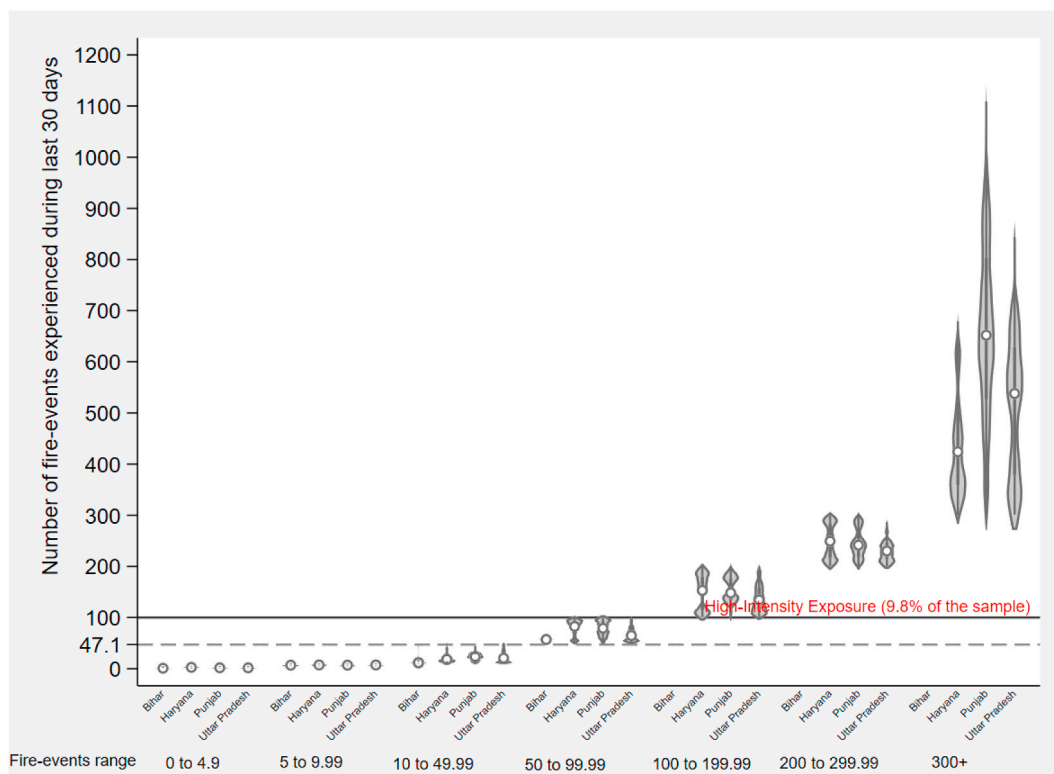
The logistic model estimates the probability of being hypertensive as a function of HIB (which is our main variable of interest) while controlling for other confounding factors. To be precise, the dependent variable in this model is  $Y$ , which is a dichotomous variable for the occurrence of hypertension and  $\text{HIB}_{icdmt}$  is the dichotomous variable which represents exposure to HIB during the last 30 days from the survey date. The  $\text{HIB}_{icdmt}$  the variable takes value 1 if the count of fire-events is greater than the cut-off value and 0 otherwise. The odds ratio for hypertension associated with HIB is captured by  $\beta$ , a value greater than 1 represents a higher probability of occurrence of hypertension for individuals who are exposed to HIB.

The models were adjusted ( $X_{icdmt}$ ) for gender, age-group, self-reported smoking and alcohol consumption behaviour, BMI and educational background of the individual, wealth index category, use of clean cooking fuel, type of residence (rural or urban) of the household and weather conditions (rainfall and temperature) for the sampled cluster during the interview month. Our estimation strategy accounted for the sampling design where sample weights were used in the estimation of the coefficients. Errors were clustered at the cluster level to account for potential correlations between observations within the same cluster. Also, we included district fixed effects ( $\rho_d$ ) to account for unobserved time-invariant regional differences like the elevation of the region,

<sup>1</sup> Details provided in sensitivity check Section 7.



**Fig. 2.** : (Left panel) NHFS-IV provides latitude and longitude of a sampled cluster (C); this location was displaced by NFHS by as much as 10 km for some clusters. Due to this displacement, the true location of the cluster is not known. However, the true location of the cluster is located within 10 km circle around the given NFHS cluster location. Exposure to high-intensity biomass burning was calculated in the 100 km radius around the cluster location (grey circle), and any exposure within a 10 km radius (white circle) was subtracted to account for uncertainty about the true location of the cluster. (Right panel) District level mean exposure to fire-events (biomass burning) in the past 30 days prior to survey for all 150 districts in our sample of the four states of North India (Haryana, Punjab, Uttar Pradesh and Bihar).



**Fig. 3.** Exposure to biomass burning for individuals in the sample. 9.8 percent of individuals in our sample were exposed to greater than 100 fire-events in the last 30 days from the date of the survey.

presence of health facilities, level of development, etc. We also accounted for the month ( $\sigma_m$ ) and year ( $\rho_t$ ) fixed effects to account for any seasonality in the data.

We also used a linear model for analysing the association between blood pressure (SBP and DBP - continuous variables) and HIB. The model controlled for same confounding factors and interacted the HIB variable with age variable to estimate the effect of HIB on SBP (and DBP) for different ages.<sup>2</sup>

## 7. Sensitivity analysis

We conducted several alternate analyses to assess the robustness of the association between HIB and hypertension. First, we include an additional variable which captures cumulative exposure to fire-events during last ten years (mean over last 10 years). This analysis has been conducted to check whether our results for acute exposure (exposure during last 30 days) is robust to controlling for chronic exposure to biomass burning. Current literature suggests that both short and long-term exposure to pollution can cause an elevation in arterial BP, the true effect depends upon the vulnerability of the individual (age, other underlying conditions etc). Short-term exposure to a pollution causing event (like high intensity biomass burning) can lead to rapid increase in BP which can elevate the blood pressure to lie in hypertensive category and can also lead to acute cardiovascular events like stroke, myocardial infarction or heart failure hospitalisation (Capello & Gaddi, 2018).

Second, we used other alternate cut-offs to define HIB to see if our results are sensitive to choosing a particular value for describing exposure to high-intensity biomass burning. These alternate cut-offs are 150 and 200 (instead of original 100 cut-off). Next, we use continuous measures for exposure to fire-events (instead of dichotomous control for exposure). These continuous measures splits the fires into *downwind* and *upwind fires*. Downwind fires refer to those fire-events from which the wind is blowing towards the cluster location while upwind fires have winds blowing away from the cluster location. Downwind fires are the ones which are responsible for deterioration of air quality (spillover effect of fire-events occurring in one location with its detrimental effect on a residential place located in the downwind direction) and thus can have a potential negative effect on health of the individuals who get exposed to them. We control for upwind fires as they serve as a proxy for the general level of agricultural or economic activity in the region which generates income and can have an indirect effect on health outcomes. Rangel and Vogl (2019) use a similar strategy in their paper as well where they analyse the effect of exposure to fire-events on child health outcomes. The use of wind direction contributes to building a causal analysis as wind direction can be considered as exogenous. Similar analysis has been used in multiple studies (Deryugina et al., 2019; Pullabhotla, 2018; Rangel & Vogl, 2019; Singh et al., 2019; Zivin et al., 2020) which assess the relationship between biomass burning or air pollution on various health or other economic outcomes.

Lastly, we also vary the radius of our analysis to alternate radii of 75 km, to establish that our results are not driven by the choice of a particular radius for analysis. Data preparation was conducted, and analysis was performed with Stata, version 15.1 (Stata-Corp, College Station, TX).

## 8. Results

### 8.1. Descriptive analysis

We first observe that individuals who were exposed to HIB during the last 30 days have a higher probability of being hypertensive. We show

<sup>2</sup> Similar age interacted model is also used in one of the subsequent analysis which uses the Logit model to assess the effect on hypertension of exposure to HIB for different age groups.

this association in Fig. 4 where we plot a quadratic relationship between our dependent variable (dichotomous variable for being hypertensive) and age of individuals for the two groups (HIB = 1 and HIB = 0). We observe that there exists a vertical gap in the plots for two groups (HIB = 1, red line and HIB = 0, dashed line) which implies that individuals from the group exposed to HIB have a greater probability of being hypertensive. This is especially true for individuals with age above 30 years.

The characteristics of the group exposed to HIB during the past 30 days and those not are summarized in Table 1. Individuals exposed to HIB had a higher prevalence of hypertension. The mean SBP and DBP were also higher for the HIB group. The mean age and age-distribution were different in the two groups. To account for these differences, we adjusted all our results by the age of an individual in our regression analysis.

The HIB group had more males and a higher BMI. A higher percentage of individuals in the HIB group reported consuming alcohol, while a higher percentage of self-reported smoking was found in no HIB group. A greater proportion of individuals in the HIB group were educated (studied till primary level) and used clean cooking fuels. More individuals in HIB group reported living in urban areas and a greater proportion of individuals in HIB belonged to the middle, richer and richest wealth category. To account for these differences between the control and treatment group we included all risk-factors in our statistical analysis.<sup>3</sup>

### 8.2. Hypertension and HIB

In this section we provide the results from our regression analysis. We begin by providing the results for a simple model where district fixed effects have not been introduced (Table 2, column 1). This was done to avoid incidental parameters problem which is present in non-linear models. The model controls for all other covariates (demographic and weather controls, month and year level seasonality). The reference group is HIB = 0. We observe that the odds ratio (OR) for HIB is 1.232 (95% CI 1.13, 1.35) which depicts that short-term exposure to HIB is associated with a higher probability of being hypertensive.<sup>4</sup>

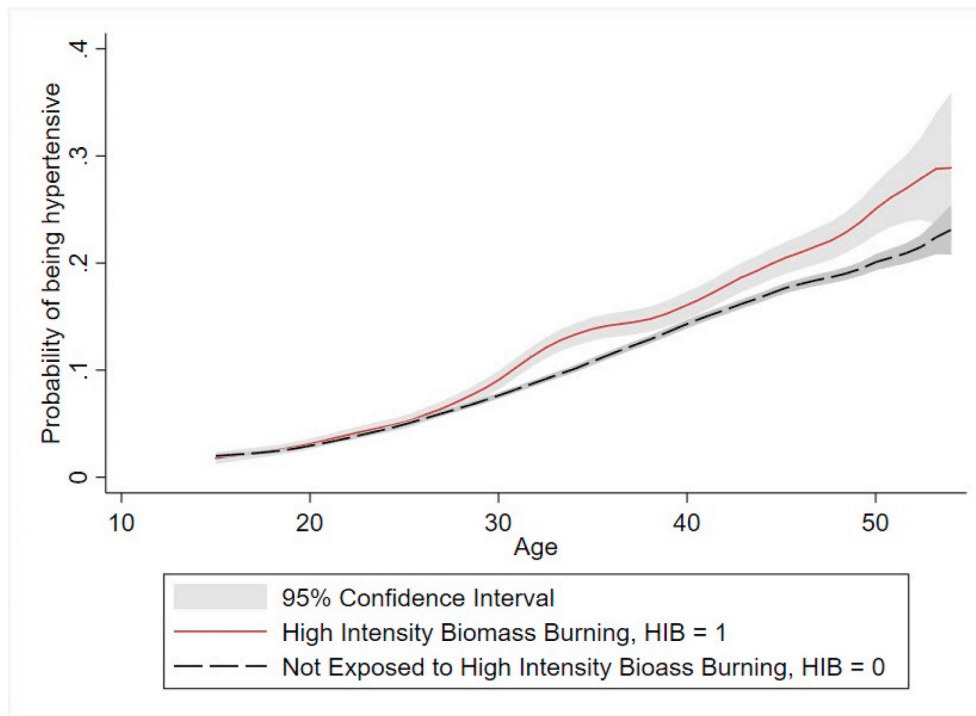
Next we present results from our main specification (equation (2)) which introduces district fixed effects along with other controls (Table 2, column 2). We observed a higher probability of hypertension in individuals exposed to HIB. The odds ratio for this multivariate analysis is found to be greater than 1 (OR = 1.15; 95% CI 1.003, 1.32). The model controlled for risk factors which include age, gender, body mass index, wealth index of the household of the individual, use of clean cooking fuel in the household, place of residence (rural or urban), educational background, smoking and alcohol consumption behaviour and weather controls for temperature and precipitation.<sup>5</sup> All errors are clustered at the cluster (PSU) level. The results provided in column 3 use an alternative clustering at district level instead of PSU level. We find that the change in clustering essentially doesn't impact the significance level of our estimates.<sup>6</sup> Columns 5 to 7 repeat the same analysis as columns 1 to 3 but use a linear probability model instead of a logit model. Essentially, we find that our estimates from the linear model predict an increase in

<sup>3</sup> Appendix Table A1 and A2 provide the details about missing observations for each variable used in construction of the estimation sample and subsequently used in analysis.

<sup>4</sup> Estimates not presented in results Table 2: The corresponding confounder-unadjusted (only fixed effects for month and year included) estimate for this model is OR: 1.39 (95% CI 1.27, 1.52).

<sup>5</sup> Estimates not presented in results Table 2: The corresponding confounder-unadjusted (only fixed effects for district, month and year included) estimate for this model is OR: 1.17 (95% CI 1.05, 1.32).

<sup>6</sup> Estimates not presented in results Table 2: The corresponding confounder-unadjusted (only fixed effects for district, month and year included) estimate for this model is OR: 1.17 (95% CI 1.03, 1.34).



**Fig. 4.** Probability of being hypertensive by age for two groups (HIB = 1 and HIB = 0; HIB takes value 1 when exposure to fire-events is greater than 100 during the last 30 days). Shaded regions depict 95% confidence intervals.

**Table 1**  
Summary statistics for the full sample.

Variable	High Intensity Exposure		Low Intensity Exposure		p-value
	HIB = 0	HIB = 1	HIB = 0	HIB = 1	
Hypertension (%)	8.1	27.3	9.9	29.8	<0.01
Systolic BP	114.3	12.9	116.0	13.2	<0.01
Diastolic BP	76.1	9.6	76.9	9.6	<0.01
Age-Group (%)					
50–54 years	0.8	9.1	1.0	9.8	<0.10
45–49 years	9.6	29.4	9.6	29.4	<0.99
40–44 years	10.4	30.5	10.9	31.2	<0.05
35–39 years	12.2	32.7	12.9	33.5	<0.01
30–34 years	13.1	33.7	14.3	35.0	<0.01
25–29 years	15.2	35.9	16.8	37.4	<0.01
20–24 years	17.0	37.6	17.9	38.3	<0.01
15–19 years	21.8	41.3	16.7	37.3	<0.01
Demographic Characteristics					
Gender = Male (%)	12.9	33.5	17.9	38.4	<0.01
Consumes alcohol (%)	3.4	18.2	4.9	21.6	<0.01
Smokes (%)	10.7	30.9	9.0	28.7	<0.01
BMI	21.4	4.0	22.5	4.4	<0.01
Educated (%)	66.6	47.2	79.7	40.2	<0.01
Uses clean cooking fuel (%)	31.0	46.2	51.8	50.0	<0.01
Rural (%)	74.9	43.4	64.0	48.0	<0.01
Wealth Index (%)					
Richest	19.7	39.8	48.7	50.0	<0.01
Richer	16.4	37.1	21.6	41.1	<0.01
Middle	17.1	37.6	13.9	34.6	<0.01
Poorer	20.5	40.4	7.6	26.5	<0.01
Poorest	26.3	44.0	8.2	27.5	<0.01
Observations	169796		18394		

Source: National Family Health Survey, 2016

probability of being hypertensive (by 1.14 percent; 95% CI 0.11, 2.18) due to exposure to high levels of biomass burning. We also provide results by using a Generalized Estimating Equations (GEE) model (Akter et al., 2018) which relies on using the correlation of observations within

a district but doesn't force the identification on within district coefficients (i.e. use to district fixed effects). We find that the magnitude of our new estimate (column 4) by using the GEE model is still significant and it is slightly higher than our original estimate (column 2).

**8.2.1. Covariates**

In line with the literature, we find (results not shown<sup>7</sup>) that as age increases the probability of being hypertensive also increases, individuals in older age groups (40 years and above) are more likely to be hypertensive than younger individuals (age 15–19 years). Males are also more likely to be hypertensive than females. Consumption of alcohol also increases the chances of being hypertensive. Furthermore, Body mass index is a strong predictor of hypertension, as an increase in BMI increases the likelihood of being hypertensive. The relationship between hypertension and wealth is found to be insignificant. Smokers generally have low body weight due to which on an average we observe that there is lesser incidence of hypertension in smokers in comparison to the non-smoking group. Educated individuals have lesser probability of being hypertensive while rural households and households which use clean cooking fuel are found to have slightly higher chance of being hypertensive.

**8.2.2. Age and gender wise result**

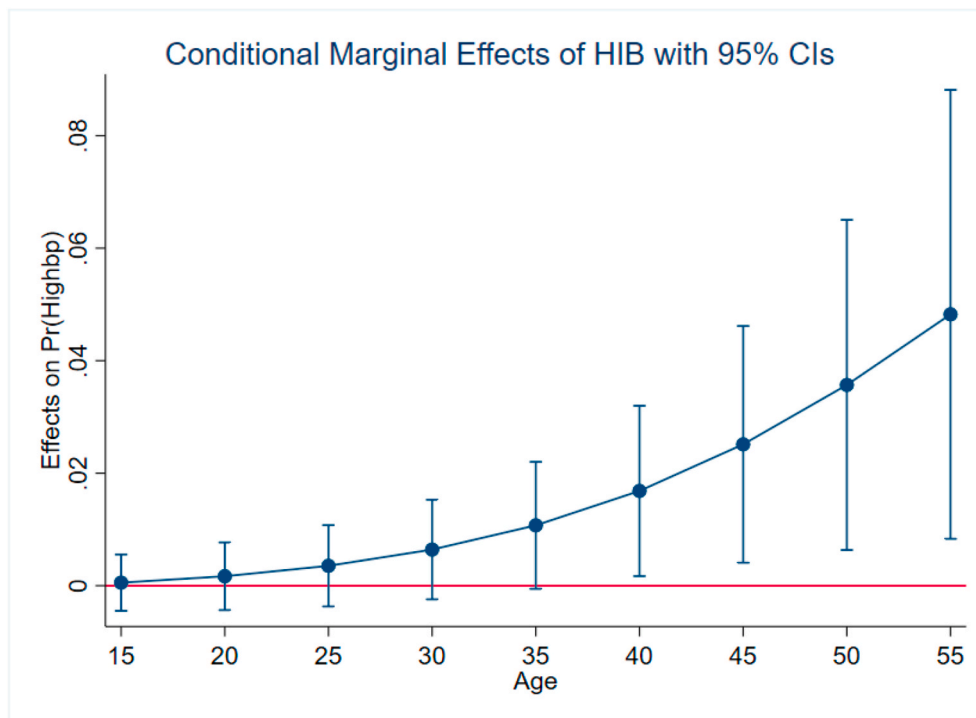
We further provide detailed results on the association between hypertension and HIB by age groups in Fig. 5. We find that exposure to HIB increases the probability of being hypertensive, this result is significant for age groups greater than 40 years. This points towards the fact that the older population is especially vulnerable to the harmful effects of exposure to HIB. We also present results broken down by gender in Fig. 6. We find similar results as before that is individuals who are aged 40 years and above (both males and females) have an odds ratio of greater than 1 for the HIB variable. NFHS-IV also provides details about the dietary intake for female respondents. We find that inclusion of

<sup>7</sup> Available on request.

**Table 2**  
High-intensity biomass burning and Hypertension.

	Logit Model (OR)			Logit GEE Model (OR)	Linear Probability Model		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Intensity Biomass Burning (Fires $\geq$ 100)	1.232***	1.153**	1.153**	1.156**	0.0130***	0.0114**	0.0114**
Individual and HH controls	✓	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓	✓
Fixed Effects							
District		✓	✓			✓	✓
Month	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓
Clustering level	PSU	PSU	District	None	PSU	PSU	District
Observations	188190	188190	188190	188190	188190	188190	188190

Note: Notation for p-values \*\*\* is  $p < 0.01$ , \*\* is  $p < 0.05$  & \* is  $p < 0.1$ . Sample weights have been used in all regressions (except for column 4). The models also controlled for other risk factors which include age, gender, body mass index, wealth index of the household of the individual, use of clean cooking fuel in the household, place of residence (rural or urban), educational background, smoking and alcohol consumption behaviour and weather controls for temperature and precipitation.



**Fig. 5.** Effect of exposure to high-intensity biomass burning (HIB) on hypertension for different ages. Vertical lines depict 95% confidence intervals for the estimate represented by circles.

controls for dietary intake which includes dichotomous controls for frequent intake of a) milk or curd, b) pulses or beans, c) green leafy vegetables, d) fruits, e) eggs, f) fish, g) chicken or meat, h) fried food and g) aerated drinks doesn't change our estimates for the female sample.<sup>8</sup>

**8.3. Systolic/diastolic blood pressure and HIB**

We now provide the results from our linear model which uses continuous dependent variables for blood pressure (SBP and DBP) rather

<sup>8</sup> Results not shown in Fig. 6 as estimates essentially remain same even after inclusion of dietary controls.

than a dichotomous variable (hypertensive or not hypertensive). The association of HIB with mean SBP (and DBP) is presented in Fig. 7. We observe that the effect of exposure to HIB on SBP (and DBP) is positive and significant for ages above 40.

**8.4. Sensitivity analysis**

We begin our sensitivity analysis by presenting results which additionally take into account chronic exposure to biomass burning (Table 3, Model 1). We find that the inclusion of chronic exposure doesn't change our estimates for the acute exposure (our estimates are actually marginally higher than our original estimate). In appendix Table A3, we provide estimates for alternate measures for cumulative exposure which

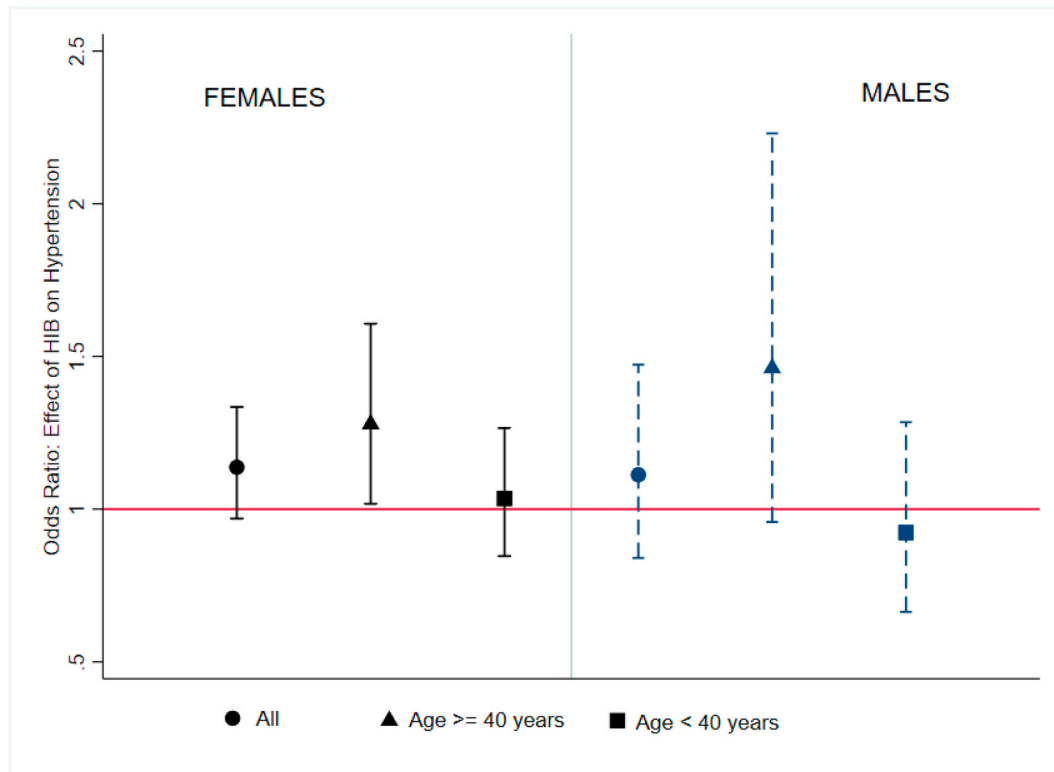


Fig. 6. The odds ratio for the relationship between hypertension and exposure to HIB for males and females for different age-groups. The model controlled for risk factors which include age, BMI, wealth index of the household of the individual, use of clean cooking fuel in the household, place of residence (rural or urban), educational background, smoking and alcohol consumption behaviour and weather controls for temperature and rainfall.

include total exposure during last 10 years, dichotomous control for exposure etc. Our results show that the estimate for acute exposure remains unchanged even after controlling for different measures of cumulative exposure to biomass burning. Next, we provide odds ratio for hypertension by using alternate cut-offs (150 and 200 fire-events) to define our main exposure variable - high-intensity biomass burning (HIB). We observed that changing the cut-off doesn't change our results, in fact the magnitude (OR from Model 2 = 1.15; 95% CI 1.05, 1.40 & OR from Model 3 = 1.15; 95% CI 1.10, 1.53) becomes larger than before (Table 3, Models 2 and 3).

Our next robustness check changed the functional form of the exposure variable and used wind direction of fire-events to assess the effect of exposure to biomass burning on cardiovascular health. We replaced our dichotomous exposure variable (HIB) with two continuous variables for fire exposure - downwind and upwind fire-events. We find (using Model 4) that with a ten-unit increase in downwind fire-events (during last 30 days), we expect to see about 1.7% increase (OR: 1.017; 95% CI 1.004, 1.03) in the odds of being hypertensive. Although the magnitude for the estimate for upwind fires is similar to the estimate for downwind fires but it is found to be insignificant. Thus, we observed a strong positive correlation between the fire-activity level and probability of being hypertensive.

Lastly, we changed our radius of analysis from 100 km to 75 km and still found that individuals who live in areas which had a higher incidence of fire-events in past 30 days are more likely to be hypertensive (OR: 1.25; 95% CI 1.06, 1.46).

## 9. Economic benefits from elimination of biomass burning

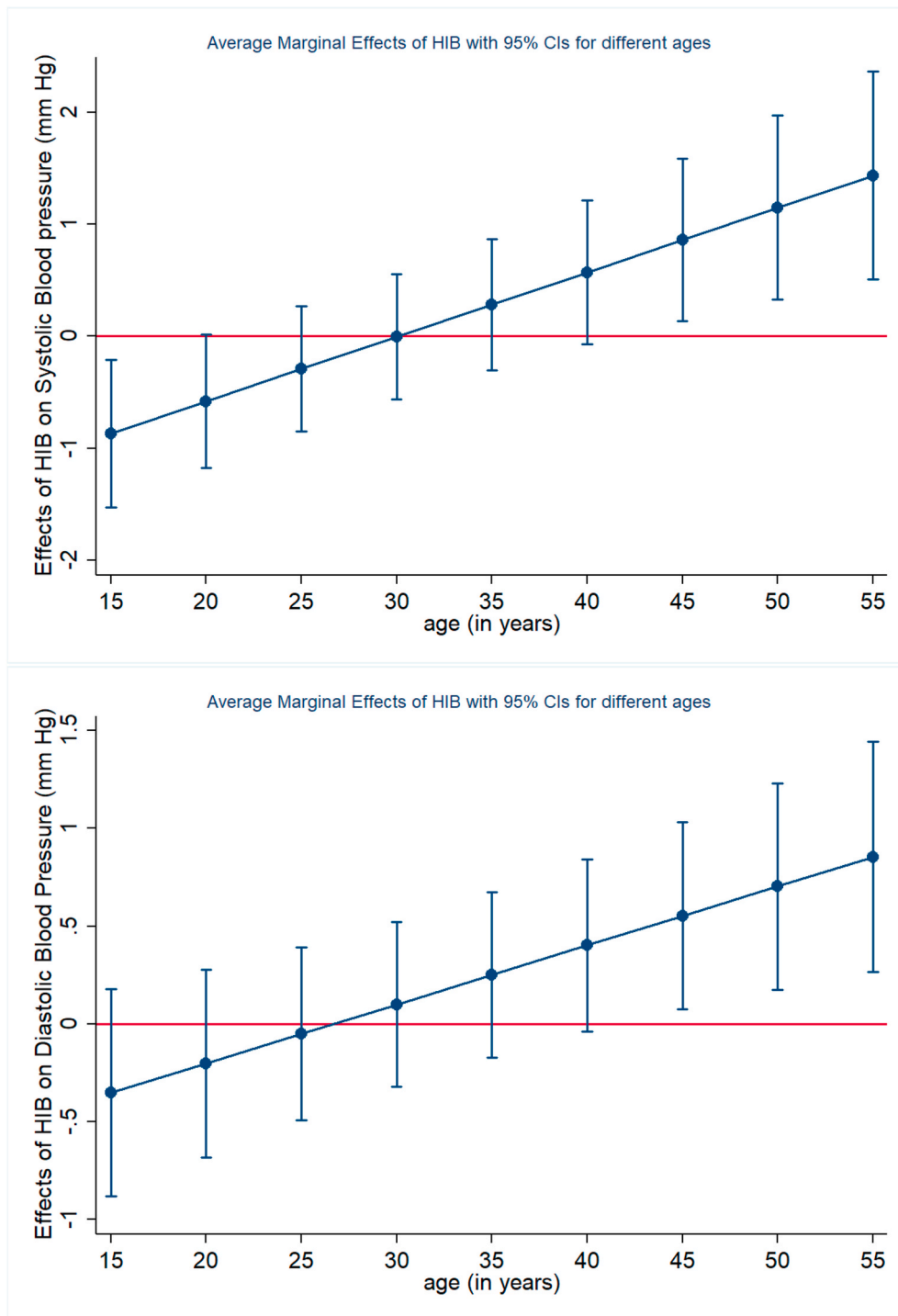
Hypertension, a leading cause of disease burden in India, leads to a deterioration in the health status of individuals. The gap between the

ideal health status and deteriorated health status due to an ailment is captured by DALY. The concept of DALYs comprises of two components - years of life lost due to early mortality because of an ailment and years lost to disability due to the consequences of an ailment. The DALYs lost due to an ailment can thus be converted into a monetary equivalent by calculating the income lost over these years due to deteriorated health status. We estimate the benefit from the elimination of crop burning (alternatively can be interpreted as avoidance of economic cost in terms of income lost over years) by using the number of DALYs associated with hypertension in various states of India.

We focused on three states - Punjab, Haryana and Uttar Pradesh which experienced a high incidence of biomass burning (Figs. 2 and 3) for this analysis. The state of Bihar is excluded from this analysis as no individuals in our sample from Bihar experienced exposure to high intensity biomass burning (HIB). We followed the strategy employed by (Chakrabarti et al., 2019) to estimate the economic benefits attributable to the elimination of biomass burning. For each of these states, we estimated the total number of cases of hypertension that would be prevented in the population if HIB was eliminated while other parameters remain unchanged.<sup>9</sup> The DALY rates for each state for cardiovascular diseases (taken from (Dandona et al., 2017)) when multiplied by state population from the Census of India gives the total years lost in a state due to hypertension. A fraction of these total years lost to hypertension in a state are attributable to hypertension due to exposure to HIB. This fraction is called the population attributable fraction (PAF), which is calculated from the model (equation (2)). In STATA, PAF is

<sup>9</sup> Since no individuals experienced HIB in Bihar so there is no need for HIB elimination, i.e. a move from HIB = 1 to HIB = 0 is not possible for observations from Bihar since already all observations have HIB = 0.





**Fig. 7.** Average marginal effect of exposure to HIB on SBP and DBP from a linear model at different ages. The model controlled for additional risk factors which include BMI, wealth index of the household of the individual, use of clean cooking fuel in the household, place of residence (rural or urban), educational background, smoking and alcohol consumption behaviour and weather controls for temperature and rainfall.

**Table 3**  
Robustness checks: Odds ratios from logit models.

	Model 1	Model 2	Model 3	Model 4	Model 5
High Intensity Biomass Burning (Fires ≥ 100)	1.154**				
Cumulative Exposure over last 10 years	1.000				
High Intensity Biomass Burning (Alternate cut-off: Fires ≥ 150)		1.212***			
High Intensity Biomass Burning (Alternate cut-off: Fires ≥ 200)			1.303***		
Downwind fireevents (continuous variable)				1.017***	
Upwind fireevents (continuous variable)				1.017	
High Intensity Biomass Burning (Alternate Radius 75 km: Fires ≥ 100)(Alternate Radius 75 km: Fires ≥ 100)					1.256***
Individual and HH controls	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓
Fixed Effects					
District	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓
Observations	188190	188190	188190	188190	188190

Note: Notation for p-values \*\*\* is  $p < 0.01$ , \*\* is  $p < 0.05$  & \* is  $p < 0.1$ . Sample weights have been used in all regressions. Downwind (upwind) fire-events refer to those fire-events for which wind is blowing from the fire-event towards (away from) the location of the sampled household. The models also controlled for other risk factors which include age, gender, body mass index, wealth index of the household of the individual, use of clean cooking fuel in the household, place of residence (rural or urban), educational background, smoking and alcohol consumption behaviour and weather controls for temperature and precipitation.

calculated by using “punaf” command. Thus, if HIB is eliminated then we save DALYs. Lastly, the DALYs saved are converted into monetary terms by multiplying by per capita state GDP (Reserve Bank of India, figures for the year 2015-16<sup>10</sup>). The per capita GDP figures are converted to Purchasing Power Parity \$ by using data from World Bank for year 2015.<sup>11</sup> We also provide an alternate estimate in USD by using exchange rate (INR-USD) for year 2015. Using a discount factor of three percent, we estimated the probable economic benefit over 5 years.

Our analysis shows that exposure to HIB does increase the probability of being hypertensive, which leads to a loss of 70–91 thousand DALYs every year.<sup>12</sup> We estimated the economic implications of biomass burning for the three states of Haryana, Punjab and Uttar Pradesh which

<sup>10</sup> Available here: <https://www.rbi.org.in/Scripts/PublicationsView.aspx?id=18474>.

<sup>11</sup> Available here: <https://data.worldbank.org/indicator/PA.NUS.PPP?locati ons=IN>.

<sup>12</sup> Lower estimate calculated as  $0.019 + 0.022 + 0.028$  Million years = 70 Thousand years (from Row 4, Table 4). Higher estimate calculated as  $0.025 + 0.028 + 0.038$  Million years = 91 Thousand years.

experienced high-intensity fire-activity (Table 3). Based on our estimates, we find that eliminating biomass burning will lead to a saving of \$1.735 to \$2.249 Billion (\$ PPP) over five years for these three states.<sup>13</sup> These cost estimates however are lower bound estimates as our analysis focuses only on summer burning of wheat crop residue<sup>14</sup> rather than winter burning when another cycle of higher amount of crop burning occurs to get rid of rice stubble (appendix Figure A1).

Although we don’t observe individuals in our sample during the winter months but we provide additional result related to winter crop residue burning and hypertension as observed during summer months based on blood pressure readings collected as part of the NFHS-IV survey. It should be noted that the mean exposure (average over all individuals living in a particular state) to total fire-events during the previous winter season i.e. months of October and November was much higher than the exposure during the summer period.<sup>15</sup> We conduct a similar logit regression analysis on hypertension (SBP ≥ 140 mm Hg and/or DBP ≥ 90 mm Hg) and high biomass burning (winter fire-events ≥ 1000) and obtain a point estimate for winter high biomass burning (OR: 1.11; 95% CI 0.79, 1.54). Further, we use estimates from this analysis to simulate for each state (which experienced this extreme level of crop burning) the number of cases of hypertension which will be avoided if extremely high levels of biomass burning (winter fire-events ≥ 1000) are eliminated by using PUNAF function in STATA. We find that an additional \$3.2 to \$4.1 Billion (\$ PPP) will be saved over five years if winter crop residue burning is eliminated from the states of Haryana and Punjab.

## 10. Discussion and conclusion

This study in 4 major north Indian states, with a combined population of over 350 million revealed that exposure to HIB in the past 30 days was associated with a higher probability of being hypertensive. To our knowledge, this is the first study to systematically examine this relationship and estimate its economic implications for India. Data on the effects of biomass burning on hypertension are sparse. Arbex et al. (2010) reported an association between air pollution from sugarcane plantation burning and hospitalizations related to hypertension in Sao Paulo, Brazil. They find that hypertension related hospitalisations due to exposure to pollution on account of sugarcane residue burning increased by 12.5% during the harvest season while the base rate was 9% during non-harvest season, this implies a 3.5% net increase due to exposure to biomass burning. Our study in comparison finds a slightly lower impact of biomass burning on hypertension (1% increase in probability of being hypertensive corresponding to the OR of 1.15). However, Arbex et al. (2010) study was limited to a small geographical area and the investigators did not quantify the burden of biomass burning and treated it as a qualitative variable comparing burning days with no burning days. Use of hypertensive emergencies as an outcome variable may have also underestimated the effects of biomass burning. In contrast, in our study, the study population is large, and we use the intensity of exposure to biomass burning.

Studies from India have assessed the influence of air pollution on hypertension. Yamamoto et al. (2014) provides a comprehensive review of these studies and includes few studies on outdoor air pollution as well. The estimates from our study are similar to those reported in a study by (Dutta & Ray, 2013) which finds that urban women from the city of Kolkata (in the Indian state of West Bengal) have a higher chance of

<sup>13</sup> The estimate in USD is 520–675 Million.

<sup>14</sup> NFHS-IV survey was conducted in these four states during summer months and hence we only capture the effect of summer burning on blood pressure recorded during these interviews.

<sup>15</sup> Mean exposure to total fire-events during the previous winter season i.e. months of October and November for the state of Punjab was 3532, for Haryana it was 1248, for UP it was 74 and for Bihar it was 7.

**Table 4**  
Economic benefit from elimination of HIB (in PPP \$ terms).

	Haryana		Punjab		UP	
	(1)	(2)	(3)	(4)	(5)	(6)
	Haryana (LCI)	Haryana (HCI)	Punjab (LCI)	Punjab (HCI)	UP (LCI)	UP (HCI)
1. DALY rates for Hypertension Diseases per person <sup>a</sup>	0.025	0.032	0.041	0.051	0.015	0.019
2. State population (in Millions) <sup>b</sup>	25.35	25.35	27.74	27.74	199.8	199.8
3. Proportion of Hypertension cases attributed to biomass burning <sup>c</sup>	0.030	0.030	0.020	0.020	0.010	0.010
4. DALYs saved (Million years) <sup>d</sup>	0.019	0.0250	0.022	0.028	0.028	0.038
5. Per capita GDP (\$/per person) <sup>e</sup>	8424	8424	6200	6200	2407	2407
6. Economic Value to DALYs saved per year (\$ Million/year) <sup>f</sup>	160.9	210.2	138.8	175.5	68.1	91.1
7. Economic Value to DALYs saved over 5 years (\$ Millions) <sup>g</sup>	759	991	655	828	321	430
Total (\$ PPP Millions)			[1735, 2249]			
Total (\$ US Millions) <sup>h</sup>			[520, 675]			

LCI, Lower 95% Confidence Interval Value; HCI, Higher 95% Confidence Interval Value DALY, disability-adjusted life years; GDP, gross domestic product.

<sup>a</sup> From The India State-Level Disease Burden Initiative, 2017. DALYs for Hypertension.

<sup>b</sup> From Indian Population Census 2011 (Office of the Registrar General & Census Commissioner 2011).

<sup>c</sup> From PUNAF after estimating equation 2.

<sup>d</sup> Row 1\*Row 2\*Row 3.

<sup>e</sup> From RBI (For year 2015-16); 19.235 Rupee = 1 PPP \$ (source World Bank Data for year 2015).

<sup>f</sup> Row 4\*Row 5.

<sup>g</sup> From Row 6 for 5 years discounted at 3% per year.

<sup>h</sup> Alternate calculation based on cost in USD. 64.12 Rupee = 1 US \$.

being hypertensive due to exposure to (short-term) particulate matter (OR = 1.39; 95%CI 1.17, 1.89). However, our estimates are much smaller in magnitude when compared with another similar study from the city of Delhi (Banerjee et al., 2012) with reported estimates as OR = 2.709 (95%CI 1.049, 6.995). Both of these studies use much smaller samples for their analysis. None of these studies have specifically evaluated the association of biomass burning with hypertension. Our study is closely related to another study which adopted a similar empirical design as ours and found an association between the incidence of acute respiratory infections and biomass burning in Northern India (Chakrabarti et al., 2019).

The limitations of our study include its observational nature with a cross-sectional design limiting the inference of our findings to an association. We measured BP during a single interview which may not be sufficient for confirming the diagnosis of hypertension with the possibility of BP changes occurring due to the acute effects of the exposure. However, the BP measurement was standardized for all individual using a single type of device and we considered the mean of the final two out of three BP readings for analysis. Another limitation of the data was that the NFHS-IV survey predominantly sampled people in the reproductive age group, with the majority of the respondents being females. The strongest association between HIB and BP was among older age groups of > 40 years consistent with published literature on greater effects of air pollution on BP with increasing age (Honda et al., 2018; Liu et al., 2017). A more representative population data, including individuals more than 55 years old, may have shown an even larger effect of biomass burning. The NFHS-IV conducted interviews for these four states from January to September, allowing capture of the effect of exposure to the summer crop burning cycle occurring in April and May. However, the highest crop burning activity in these areas typically occurs in October and November after the rice harvest season. Thus, again the overall impact may have been greater if the individuals were surveyed during the winter burning season.

Our study also provides an analysis related to the economic costs (alternatively interpreted as economic benefits which will accrue if biomass burning is eliminated) associated with loss of DALYs. The calculated impact of eliminating biomass burning is large. India thus needs effective policies regarding regulation and management of

biomass burning. The policy instruments should address the knowledge barrier in adoption of new clean technologies for managing crop residue and they should provide greater financial support for buying new machinery (Happy-seeder this is an alternative to combine harvester, it leaves rice residue in form of a mulch on the farm which doesn't hamper wheat crop sowing and hence doesn't require burning). In addition to this farmers should be encouraged to sell their residue for alternative purposes like use of rice pellets for power generation, use of stubble as fodder for cattle etc. Lastly, the policy of zero-tolerance towards crop burning has been found to be ineffective in the past. The future policy scenario should combine zero-tolerance policy with greater amount of monetary support by the government for renting/buying new machinery, financial incentives for zero-burning and information dissemination about harmful health effects of crop burning to the farmers. An optimal mix of these policy instruments will encourage farmers to move away from crop burning practice.

The current policy scenario on paper is in line with what is needed. For example, the government has committed itself to subsidise the use of happy-seeder technology. However, the uptake of this technology remains quite low due to the need for a high initial investment in the machinery (Gupta, 2011; Shyamsundar et al., 2019). Under a new revised scheme, the government has allocated 1150 crore INR (125 million USD) for curbing crop burning in these states by adopting a three-pronged approach - providing machines at a subsidized rate, higher monitoring effort on part of government officials and creating greater awareness about harmful effects of crop burning by information campaigns (MoAFW, 2019). The cost of these interventions is much lower in comparison to the benefits which would accrue if biomass burning is eliminated, but still due to limited financial support and weak enforceability the policy has not eliminated crop burning in North India.

To conclude, we found that individuals exposed to HIB burning had a higher prevalence of hypertension. Biomass burning also led to higher systolic and diastolic blood pressures in the older cohort. An estimated economic benefit of over \$1.7 Billion (in PPP terms) over 5 years may accrue by a decrease in the prevalence of hypertension if biomass burning is eliminated. The results of our study emphasize an urgent need for policy decisions to contain biomass burning and thus reduce its harmful effect on health.

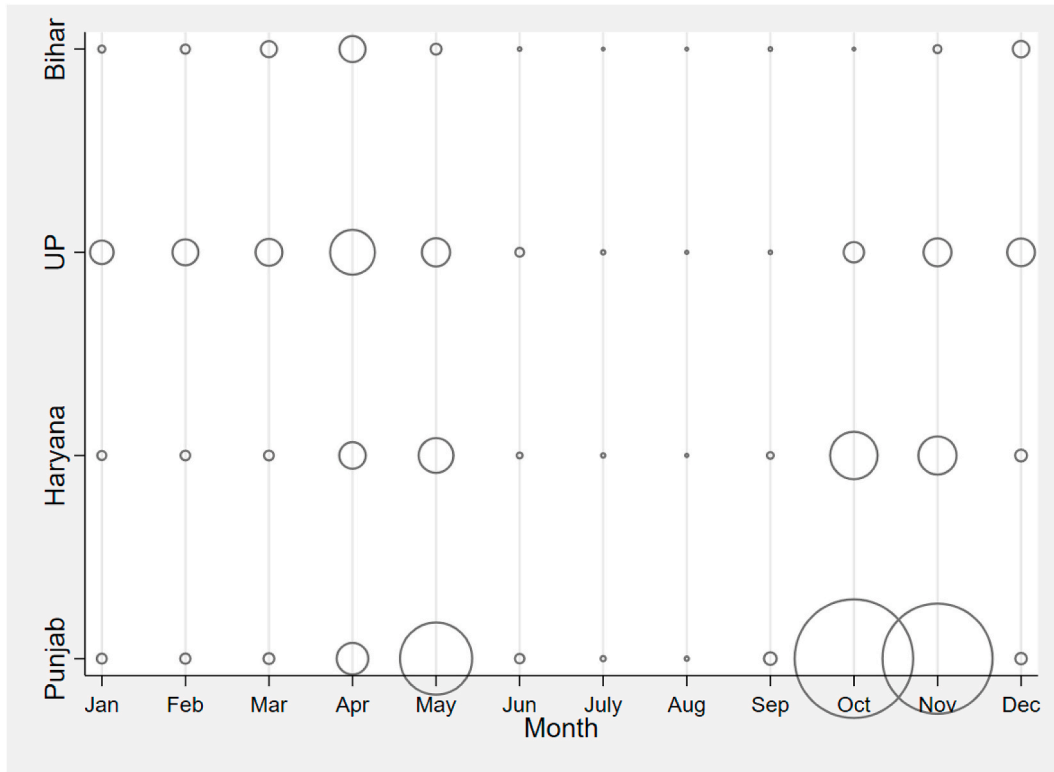
**Declaration of competing interest**

The authors declare that they have no conflict of interest.

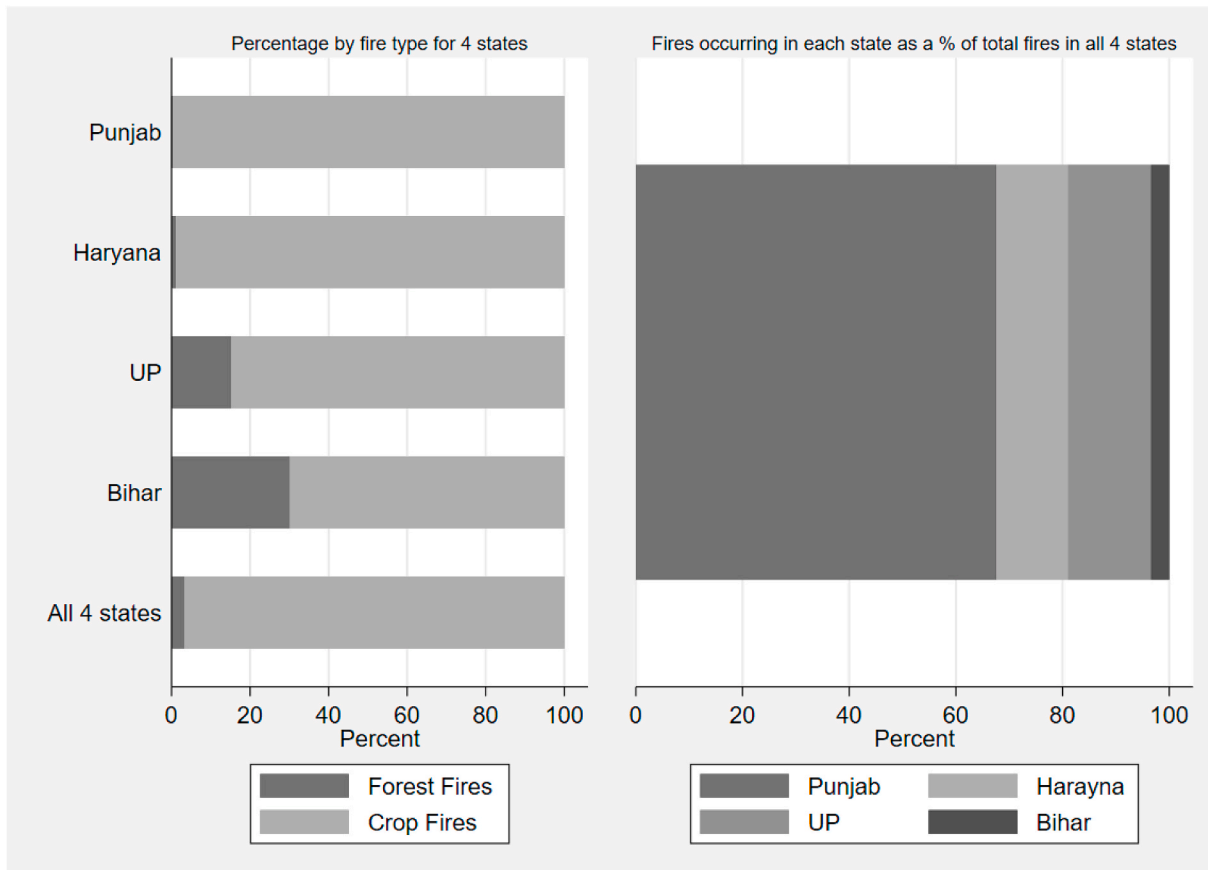
**Acknowledgements**

MODIS fire count data are available from <https://firms.modaps.eosdis.nasa.gov/map>. Sagnik Dey acknowledges the support for Institute Chair position.

**Appendix**



**Fig. A1.** Seasonality of fire-activity: Fires occurring in each state in each month (Monthly figures have been averaged over data for years 2006–2016). Size of the bubble depicts number of fires, bigger bubble corresponds to higher number of fires.



**Fig. A2.** (Left Panel) Percentage of different fire-events (forest fire or crop fire) for 4 North Indian states for years 2015 and 2016. This segregation of fires was done by projecting geo-coded fire-events on to Land Mask cover for India to determine which fires took place in crop land versus forest land. (Right Panel) Percentage of fires contributed by each state to the total fires detected for years 2015 and 2016.

**Table A1**  
Sample deductions for main outcome variable

	Outcome variable - Hypertension	Observations Left
Full Sample	211152	
Missing GPS Data	219	210933
(dropping) Individuals who take medicine for hypertension	5556	205377
(dropping) Females who are pregnant	10695	194682
Outlier BP readings	405	194277

Note: Total observations left = 194277, 18824 belong to the exposed group (HIB = 1) and 175453 belong to the unexposed group (HIB = 0).

**Table A2**  
Sample details: Missing observations for variables used in analysis

variable	Source	Measurement	HIB = 1		HIB = 0	
			Total	Missing	Total	Missing
Systolic BP	NFHS-IV	mm Hg	18824	340	175453	3450
Diastolic BP	NFHS-IV	mm Hg	18824	384	175453	3885
Hypertension	Constructed using SBP and DBP readings by following ESH/ESC 2018 guideline	Dummy	18824	384	175453	3940
Age-Group (5-year bins)						
50–54 years	NFHS-IV	Dummy	18824	0	175453	0
45–49 years	NFHS-IV	Dummy	18824	0	175453	0
40–44 years	NFHS-IV	Dummy	18824	0	175453	0
35–39 years	NFHS-IV	Dummy	18824	0	175453	0
30–34 years	NFHS-IV	Dummy	18824	0	175453	0
25–29 years	NFHS-IV	Dummy	18824	0	175453	0
20–24 years	NFHS-IV	Dummy	18824	0	175453	0
15–19 years	NFHS-IV	Dummy	18824	0	175453	0
Demographic Characteristics						
Gender = Male	NFHS-IV	Dummy	18824	0	175453	0
Consumes alcohol	NFHS-IV	Dummy	18824	0	175453	0

(continued on next page)

**Table A2 (continued)**

variable	Source	Measurement	HIB = 1		HIB = 0	
			Total	Missing	Total	Missing
Smokes	NFHS-IV	Dummy	18824	0	175453	0
BMI	NFHS-IV	kg/m2	18824	277	175453	2165
Educated	NFHS-IV	Dummy	18824	0	175453	0
Uses clean cooking fuel	NFHS-IV	Dummy	18824	0	175453	0
Rural	NFHS-IV	Dummy	18824	0	175453	0
Wealth Index						
Richest	NFHS-IV	Dummy	18824	0	175453	0
Richer	NFHS-IV	Dummy	18824	0	175453	0
Middle	NFHS-IV	Dummy	18824	0	175453	0
Poorer	NFHS-IV	Dummy	18824	0	175453	0
Poorest	NFHS-IV	Dummy	18824	0	175453	0
Weather variables (scaled by a factor of 100)						
Temperature	ECMWF	Kelvin	18824	0	175453	1313
Rainfall	ECMWF	Meters	18824	0	175453	3

**Table A3**

Odds Ratios for Cumulative and Acute Exposure to Fire-events

	Cumulative Exposure				Acute + Cumulative Exposure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Intensity Biomass Burning (Fires >100)					1.154**	1.154**	1.152**	1.152**
Cumulative Exposure Continuous Measure (Mean fires per year: Average for last 10 years)	1.000				1.000			
Cumulative Exposure Continuous Measure (Total exposure to fires during last 10 years)		1.000				1.000		
Cumulative Exposure Dichotomous Measure (Dummy for Top Decile for Mean fires per year: Average for last 10 years)			1.105				1.102	
Cumulative Exposure Dichotomous Measure (Dummy for Top Decile for Total exposure to fires during last 10 years)				1.105				1.102
Individual and HH Controls	✓	✓	✓	✓	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓
Fixed Effects								
District	✓	✓	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Observations	188190	188190	188190	188190	188190	188190	188190	188190

Note: Notation for p-values \*\*\* is  $p < 0.01$ , \*\* is  $p < 0.05$  & \* is  $p < 0.1$ . Sample weights have been used in all regressions. The models also controlled for other risk factors which include age, gender, body mass index, wealth index of the household of the individual, use of clean cooking fuel in the household, place of residence (rural or urban), educational background, smoking and alcohol consumption behaviour and weather controls for temperature and precipitation.

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