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Crop burning and forest fires: Long-term effect on adolescent height in India

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ABSTRACT

This paper examines the effect of biomass burning on adolescent health in India. The biomass burning problem is quite acute especially in North India, with some states experiencing forest fires and few states actively engaging in crop burning practice. We combine remote sensing data on biomass burning events with a pan-India survey on teenage girls (TAG survey). We exploit regional and temporal variation in our data to establish the link between occurrence of extremely high levels of biomass burning during early life and adolescent height for girls in India. Our results indicate that exposure to extremely high level of biomass burning during prenatal and postnatal period is associated with lower height (by 0.7 percent or 1.07 cm) later in life. Girls from North India are found to be especially vulnerable to the harmful effects of exposure to biomass burning.

1. Introduction

Air pollution is a world wide problem which adversely affects both natural world and human capital. In case of India the air pollution problem is particularly acute. More than fifty percent of the Indian population resides in areas with air quality breaching the safe standards set by the national government (Greenstone et al., 2015). The disease burden is also estimated to be huge with more than 1.1 million deaths attributable to air pollution in India in 2015 (HEI, 2018). There are multiple sources of air pollution in India which include transportation, coal fired power plants, agricultural burning, forest fires, industrial pollution and use of unclean cooking fuel by households. The contribution of these sources of pollution to overall air quality is not unique and takes different forms for different states and even differs by season. The practice of agricultural burning is quite prominent in many states of India with few North Indian states conducting huge amount of controlled burning on their farmlands. Another source of vegetation or biomass burning is forest fires which is also prevalent in many states of India. These biomass burning events release harmful pollutants which affect human health in myriad ways. In this paper, we analyze the effect of exposure to biomass burning experienced during early life (prenatal and postnatal period)

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on later life health outcome for adolescent girls in India. Specifically, we focus on the height of adolescents and associate it with exposure to high level of biomass burning faced during early life.

Biomass burning is a major source of pollution as it releases harmful pollutants like Carbon Dioxide, Carbon Monoxide, Sulphur Oxides, Methane, Nitrous Oxide and particulate matter (PM) in the atmosphere (Kaskaoutis et al., 2014; Gadde et al., 2009). Exposure to these pollutants has been shown to affect human health adversely. The adverse effect of major biomass burning events have been the focus of many studies which assess the impact on mortality outcomes, cardiac health, respiratory health, adult height, etc. (Douglass, 2008; Jayachandran, 2009; Rangel and Vogl, 2019; Rosales-Rueda and Triyana, 2019; TanSoo and Pattanayak, 2019).

While there are a lot of studies which have explored the connection between biomass burning and deteriorating air quality in India (Jethva et al., 2019; Bikkina et al., 2019), there are only handful of studies which have focused on its health impact on Indian population and these studies mostly explore the short-term health effect of biomass burning like occurrence of acute respiratory infections, cardiovascular health, infant mortality and child height for children below age 5 years (Chakrabarti et al., 2019; Singh et al., 2021, 2019; Pullabhotla, 2018; Spears et al., 2019; Goyal and Canning, 2017). The long term health impact of these common agricultural practices (like crop burning or clearing forests by burning) have not received much focus in the literature. In our paper we attempt to bridge this gap by providing evidence for the link between biomass burning experienced during early life and later life outcome as measured by height of an individual. We choose height as our outcome variable as height has been shown to be correlated with important later life outcomes related to human capital like adult mortality, cognitive ability, educational attainment, adult income, and off spring birth weight (Victora et al., 2008; Mendez and Adair, 1999).

We combine remote sensing data on biomass burning events with survey data on teenage girls in India (TAG Survey, 2016–17). This survey captured anthropometric measure for height of a girl, her residential location and date of birth along with other demographic characteristics of her household. In our analysis, we assess whether adolescent height of a girl is associated with exposure to high levels of biomass burning experienced during the in-utero period and postnatal period while controlling for other confounding factors. Our analysis shows that exposure to extremely high level of biomass burning during early life is negatively associated with future health outcome as measured by height of an girl in adolescence. We find that height of an adolescent girl is lower by 1.07 cm or 0.7 percent for girl who were exposed to high levels of biomass burning during early life. The effect is concentrated mostly in North Indian states which routinely conduct crop burning or face forest fires. These results are especially important given the link between height and other human capital outcomes (like educational attainment, cognition, disease vulnerability, etc.).

The paper follows the following structure. The next section provides a literature review and Section 3 provides a background on biomass burning in India. Section 4 describes the various datasets that we use in our analysis. The next section presents the empirical methodology that we follow and is followed by results in Section 6. Section 7 concludes and discusses some policies which have been used by the government to contain biomass burning problem in India.

2. Literature review

The early life period which comprises of in-utero and postnatal period (six months after birth) has been recognized as a period of special significance as it critically determines later life outcomes ("fetal origins" hypothesis by Almond and Currie (2011)). Currie and Vogl (2013) and Currie et al. (2014) provide a review of these early life shocks (like famine, drought, war, air and water pollution) on various outcomes; broadly summarised, these shocks negatively affects human capital as captured by adult cognition, years of schooling, literacy status, adult height and stunting measures; and increase the likelihood of presence of birth defects, prevalence of heart disease and obesity. A major part of the literature focuses on learning outcomes (test-scores) and earnings which are negatively affected due to in-utero exposure to pollution (Bharadwaj et al., 2017; Isen et al., 2017; Sanders, 2012).

One important source of air pollution is biomass burning. Major biomass burning events like wildfires have been the focus of multiple studies. The Indonesian wildfire of 1997 has been shown to have multiple adverse health effects like increase in infant mortality, reported asthma cases, respiratory problems, pre-term births, etc. (Jayachandran, 2009; Rukumnuaykit, 2003; Kunii et al., 2002; Frankenberg et al., 2005; Barber and Schweithelm, 2000). Studies on Californian wildfires (Holstius et al., 2012) and Australian wildfires (O'Donnell and Behie, 2015) have shown that birth weights for children get affected in response to the exposure to wildfire incidents. Additionally, Lai et al. (2017) demonstrated that agricultural fires in China affect human cognition. Douglass (2008) has shown that wildfires in US affect respiratory health, cardiovascular problems and even led to loss of work days.

Recently few papers have established that in-utero exposure to biomass burning events and pollution (Pullabhotla, 2018; Rangel and Vogl, 2019; Rosales-Rueda and Triyana, 2019; Singh et al., 2019; TanSoo and Pattanayak, 2019) negatively affects birth weight, infant mortality, child height, lung capacity and long-term health outcomes like adult height. A recent paper by Chakrabarti et al. (2019) shows that exposure to intense agricultural crop burning in Haryana increased the risk of acute respiratory infections by 3 times, this effect was found to be present for both children and adults (Gupta et al. (2016) find similar results in their study as well). Additionally, exposure to pollution causing events affect expecting mother's health adversely (Rosales-Rueda and Triyana, 2019). This suggests that potentially fetal growth can be negatively affected as well. Other studies from India have found that exposure to pollution during critical phases of development negatively affect child health outcomes related to height for children under 5 years of age. (Singh et al., 2019) show in their paper that during

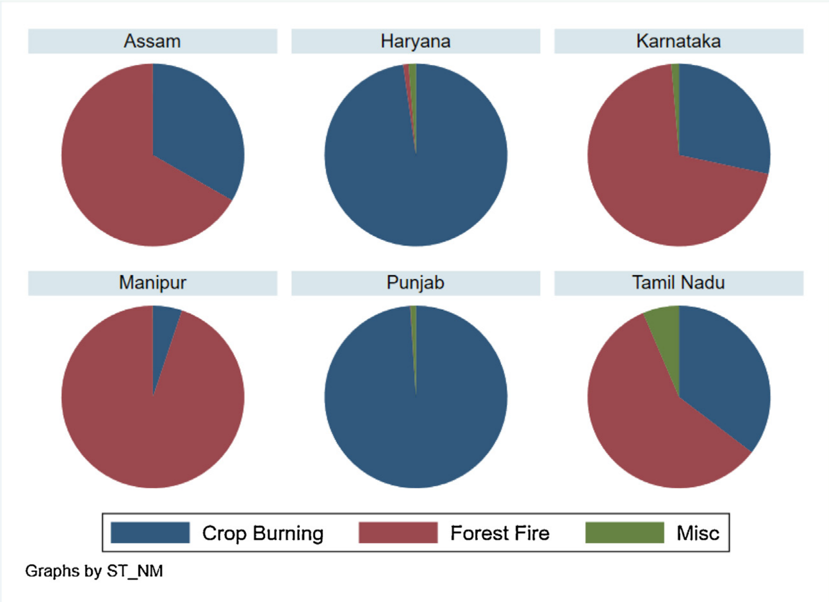

Fig. 1. Biomass burning events for years 2001 to 2005 split into type of fires – crop fires, forest fires or miscellaneous for few states from our sample.

the first trimester an increase in exposure to pollution decreases height-for-age for children. Similarly, (Spears et al., 2019; Goyal and Canning, 2017) find that exposure to pollution during early-life is associated with a decrease in height-for-age. While seasonal biomass burning problem is of great concern for a developing nation like India its *long-term* consequences on health have not been studied. In this paper, we extend this literature by focusing on early life exposure to biomass burning (crop burning and forest fires) in India and link it to long term health outcome which is captured by adolescent height. Additionally, the literature which has explored the long-term effects of biomass burning on adult height belongs to only one region (Indonesia) and focuses on a single event (1997 Indonesian forest fires) rather than looking at recurring biomass burning events. Our paper captures the exposure to biomass burning events which take place throughout an year and assesses its association with later life outcome (adolescent height).

3. Background

India has a substantial amount of land under cultivation (60%) and under forest cover (25%) (Source: World Bank Indicators[1]), with majority biomass burning events taking place in these areas (based on author's calculation, refer Fig. 1). Over the past few decades, Indian agriculture has been marked with expansion of irrigation facilities, adoption of high yield variety seeds and increased mechanisation (like use of combine harvester). A combination of these factors led to adoption of multi-cropping system by farmers which leaves little time in between the harvest of one crop and sowing of another (Gupta et al., 2004). In this scenario, crop residue burning thus emerged as the quickest and cheapest way to get the farm ready for the next crop. Cereals are the prime contributor to crop burning activity in India, with rice and wheat crop residue burning forming the major chunk of residue burning process (Jain et al., 2014). Two major residue burning seasons are thus related to crop harvest seasons: kharif crop harvest (rice stubble burning) which takes place in the months of October and November; and rabi crop harvest (wheat straw burning) which happens in the months of March to April (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, Bihar and West Bengal.

Biomass burning in India is not limited to just crop residue burning, it covers forest fires as well (Vadrevu et al., 2012). Forest fires or wildfires are caused by various factors acting in conjunction with each other. These factors include availability of biomass (dry vegetation) and appropriate climatic conditions (high temperature, low pressure, windy conditions). Forest Survey of India (2017) lists vulnerable months for each state when forest fires are most likely to happen, which mainly span the high temperature months from March to May. Wildfires happen due to both intentional and unintentional human activity. In North Eastern states (like Assam, Mizoram, Nagaland, Tripura, Meghalaya, Manipur) and in states along the Eastern Ghats (Odisha and Andhra Pradesh), slash and burn activity is rampant wherein vegetation in forests is cut (slashed) and then burned to clear the piece of land for human use (Venkataraman et al., 2006). In a lot of cases unintentional human

[1] https://data.worldbank.org/indicator/AG.LND.AGRI.ZS.

activities like leaving active cigarette butts behind in open forests lead to forest fires. Other natural factors which cause forest fires include lightening which produces a spark to start a fire in dry vegetation.

Different states have different composition of biomass burning events. To analyse this further, we split fire-events into forest fires and crop fires for all states of India. This has been conducted by projecting geo-coded fire events onto land mask cover for India to categorise each fire event as an event which happens in a forest area versus cropped area. A raw count of biomass burning events in India shows that crop residue burning and forest fires contribute 52 percent and 45 percent respectively to the total amount of biomass burning events which took place from 2001 to 2005. In Fig. 1, we show this split for few states. We observe that while almost all of biomass burning events are crop fires in case of Punjab, on the other hand in a state like Assam most of the biomass burning events are forest fires. Biomass burning is also seasonal in nature, in appendix Table A1 we show the extent of mean biomass burning in different states of India for different months for years 2001 to 2005. We notice extremely high levels of biomass burning in months of October and November for Punjab which corresponds to the rice harvest season. During the wheat crop harvest alot of farmers also burn crop residue (months of April and May). Another peak is observed for many North Eastern (Mizoram, Assam, Manipur, Meghalaya, etc.) states during summers (February to April) which is a vulnerable forest fire period and also a time when farmers clear forest areas to make them ready for cultivation.

4. Data

We now describe various datasets which have been combined together at village level for our analysis:

4.1. Fire-events

Our source of biomass burning events (called fire incidents) comes from NASA's Fire Information for Resource Management System (FIRMS) data which captures real-time active fire locations across the globe. The FIRMS data that we use is called MODIS (shortform for MODerate Resolution Imaging Spectro radiometer) data and it records fire incidents at pixel level where each pixel is identified by a latitude and longitude reading. Each latitude (and longitude) is the centroid of a one kilometre pixel (1 km $\times$ 1 km in size). This data records not just the location of a fire but also the brightness (temperature) of fire (in Kelvin units) and date and time when the incident was picked by the Terra satellite.[2] The MODIS data is available on a daily basis since November 2000 and NASA reports that the fires captured by this dataset are mostly vegetation fires.[3]

Fire-events are sourced from satellite images that are divided into pixels. Number of fire-events refers to the count of pixels. These are biomass burning events that include both crop residue burning and forest fires. Further, when fire incidents are recorded then each of them has a confidence value ranging from 0 to 1 (interpreted as probability of occurrence of an actual fire-event) which depicts the quality or reliability of the observation. We use this geo-coded dataset on occurrence of fire-events and describe the steps we followed to combine it with our survey dataset in the next section.

4.2. Demographic data

The demographic data we use comes from a new pan India survey of Teenage girls in India (TAG Survey) which was conducted in 2016–17. This is the first survey focusing on teenage girls (aged 13 to 19 years) which covers all major states and union territories of India. It followed a multi-stage sampling where first each state was divided into rural and urban areas, and then villages (for rural areas) and census enumerations blocks (for urban areas) were selected. These villages or census enumerations blocks form the primary sampling unit (PSU) in the survey. In all the selected villages/blocks, complete listing of the households with at least one respondent was carried out. These lists of the households form a sampling frame for the selection of households. From the list of households, 20 households were selected by systematic random sampling.[4]

This dataset contains information about the place of residence, that is the state of residence of the household and additionally it captured the identity (name) of the PSU (village name or census enumeration block name). These PSU names are used to fetch the geo-codes of the PSU using the village shape file for India.

Demographic information about the sampled households is also captured in this survey along with detailed information about teenage girl's date of birth and educational status of her parents. Anthropometric measures were also collected which include height (in cm) for each respondent. Three readings were taken for measurement of height, we use a mean of these three readings for height of a girl for our analysis.

We use the geo-codes of sampled PSUs in TAG dataset and calculate the total number of fire-events occurring in the 75 km radius around the PSU location. This total count of fire-events is arrived at by weighing each fire-event by its confidence value.[5] Thus the final measure of exposure to fire-events is the confidence weighted count of fire events (Rangel and Vogl,

[2] An observation for a fire incident in MODIS data for a latitude and longitude does not necessarily mean that the size of the fire is one square kilometre, but it means that atleast one fire is located within this fire pixel (under good conditions the satellite can detect fires as small as 100 m^2).

[3] As reported in NASA FIRMS data frequently asked questions here – https://earthdata.nasa.gov/faq/firms-faq.

[4] Only those households were chosen who had atleast one teenage girl, in case the number of such households was low in a village then few villages were merged together to form a primary sampling unit or PSU from which a total of 20 households were randomly surveyed.

[5] In one of the robustness checks, we alternatively weigh the fires by their brightness instead of confidence value. This essentially captures the intensity of fires.

2019) which took place in 75 km radius around the PSU location during the *early life* of a teenage girl. Following TanSoo and Pattanayak, 2019, we define early life as the period from prenatal (9 months in-utero period) to postnatal period (6 months after birth). We use the month and year of birth of a teenage girl and impute exposure to fire-events during the prenatal period by assuming the gestational age to be nine months or ≈39 weeks (Brainerd and Menon (2014), Rosales-Rueda and Triyana (2019) use a similar assumption in their analysis as well).[6] We define a dichotomous variable – High Intensity Biomass Burning (HIBB) for the early-life period (first 15 months) which takes value 1 if the total exposure to probability weighted count of fire-events lies to the extreme right of the exposure distribution (top 5% observations) and 0 otherwise.[7] Similar dichotomous variables are also constructed for the pre-natal (9 months duration) and post-natal (6 months duration) period which together cover the entire early-life period.

We also assume that the current residence of the girl is same as the place of her early life i.e. prenatal to postnatal period. We find support for this assumption in the literature as well, Munshi and Rosenzweig (2009) use a panel data and show that low rates of out-migration are due to the presence of caste-based insurance networks in India. Gupta and Spears (2017) also show that threat of endogenously pollution-avoiding migration is really low, the authors use 2 rounds of Indian Human Development Survey (IHDS panel dataset) and find that less than 2 percent households migrated between 2005 and 2012. Additionally, we use National Family Health Survey-IV round for India and find that the average duration of residence for households at the current place is 15 years.

We now explore the spatial patterns of biomass burning in India. Fig. 2 provides a heatmap of total exposure to biomass burning experienced during early life by teenage girls in various districts of India. We plot the mean exposure to biomass burning events in the local area (this is the average of total exposure for all girls belonging to the same district). A darker shade represents higher exposure to biomass burning events, we observe that North Indian states of Punjab and Haryana have the highest levels of biomass burning. Some North Eastern states (Assam, Mizoram, Manipur, Tripura, Nagaland) also exhibit high levels of biomass burning. Districts belonging to states like Gujarat, Rajasthan and Jammu and Kashmir have very low fire-activity (lighter shade). Districts in South Indian states have much lower exposure to fire-events which is represented by lighter shades of blue and green.

4.3. Weather data

To account for weather conditions, we also use gridded rainfall and temperature data from MODIS-Terra LST dataset available at 0.5 * 0.5 degree resolution (50 km*50 km grid). We calculate the mean of all grid points falling within the 75 km radius of the PSU location. These grid point values are weighted by inverse of distance between the grid point and the PSU location. These mean rainfall and temperature measures are constructed for each month in the early life period for a girl, the final measure used in our analysis calculates the average over all 15 months of the early life period (9 months of prenatal + 6 months of postnatal period) of a teenage girl.

We now describe the steps followed to construct our final estimation sample. The sample selection steps have been outlined in Fig. 3. We begin with a total sample of 61,672 girls from the TAG survey. We retain 22,443 girls from this sample for our analysis due to NASA's FIRMS data availability constraint.[8] NASA data on fire-events is only available after November 2000 so we focus on girls who were born after October, 2001 so that exposure to biomass burning events information is available for their complete in-utero period. Our sample size further reduces to 20,022 based on availability of data for background characteristics and weather information (for rainfall and temperature). Our final estimation sample further reduces to 19,798 girls as 224 girls are dropped from analysis as they are singleton observations based on the empirical strategy followed by us (described in the next section). Our final sample had 3276 PSUs with information for 19,798 teenage girls aged between 13 and 15 years.[9]

Summary statistics

We provide a summary of our estimation sample in Table 1. The average age of a sampled girl is 13.7 years. In both North and South India, almost 30% of the sample belongs to marginalized group of scheduled castes and scheduled tribes. Majority of our sample follows Hindu religion and belongs to rural areas, with average household size being 5.8 members. North Indian households are slightly bigger with a household size of 6.19. We see an almost equal split between wealth categories in Northern states, but Southern states have more households belonging to the middle or rich categories. Parents are more educated in southern states in almost all categories (four categories) in comparison to North Indian states. The exposure to fire-events during early life is significantly higher for Northern states in comparison to Southern states, where both crop

6 In our robustness checks we alter the gestational age to 35 and 38 weeks as well.

7 In our robustness checks we provide results for alternate cut-offs used for construction of HIBB variable.

8 The TAG survey focused on teenage girls and the original sample surveyed teenage girls who were 12 to 20 years old in 2016–17. When we combine survey data with data on fire-events then the resulting sample retains girls who are 12 to 15 years old in 2016–17, i.e. they were born between 2001 and 2004. We lose older girls in our analysis as fire data is not available for their early life time period. Girls in the sample are born between October 2001 and October 2004, correspondingly their exposure during early life period of 15 months (9 months of in-utero exposure and 6 months of postnatal exposure) ranges from Jan 2001 to March 2005.

9 237 girls out of the total sample of 19,798 girls are aged 12 but have almost turned 13 which is the reason behind their inclusion in the TAG Survey which focuses on teenage girls.

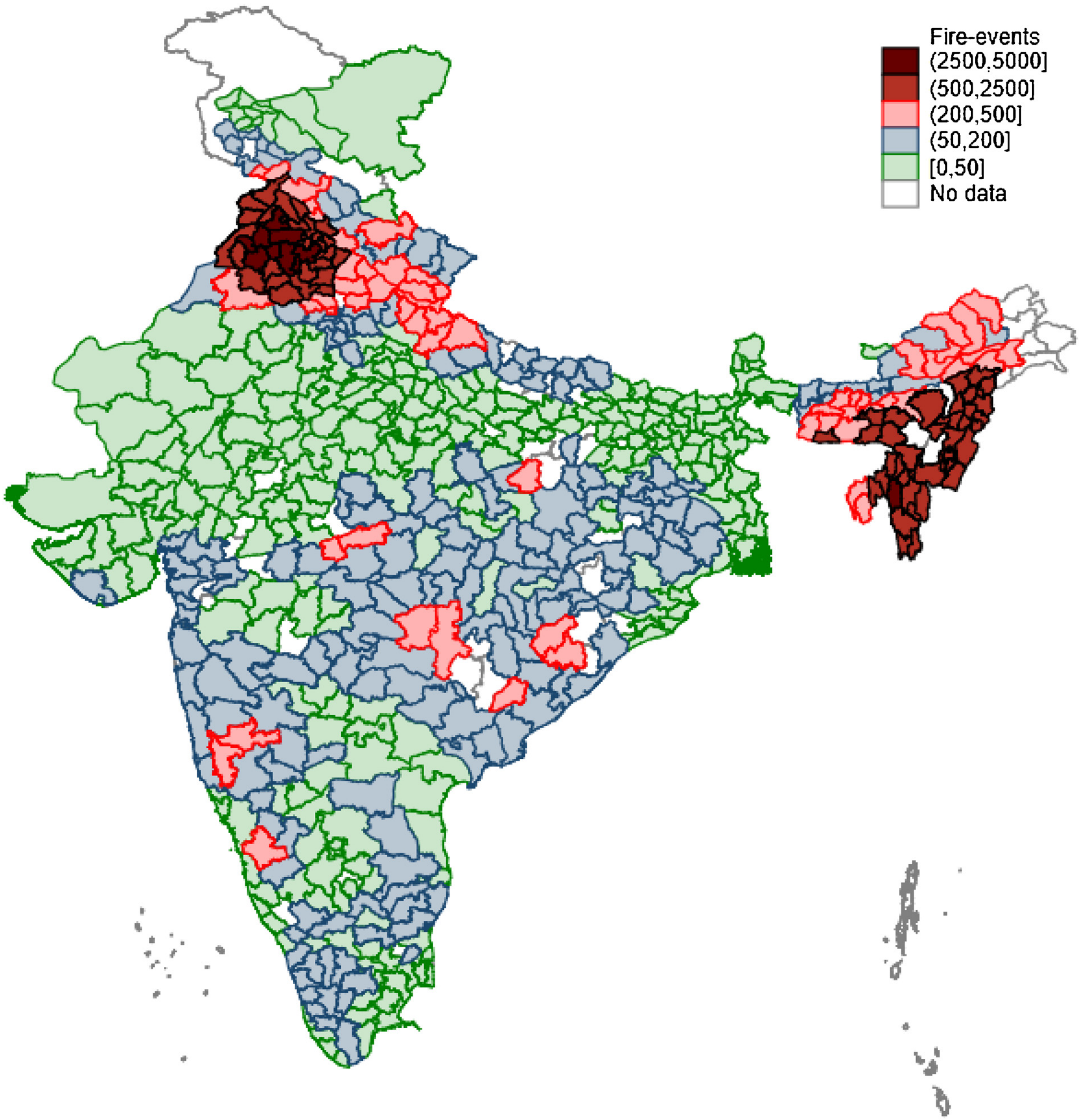

Fig. 2. District-wise mean exposure to fire-events during early life for teenage girls in India.

burning and wildfires are not that common. Finally, we do observe that a teenage girl from South India is significantly taller than a North Indian girl. We explore the association between teenage height and biomass burning in next section where we discuss the empirical methodology.

5. Empirical model

We seek to investigate whether early life exposure to high intensity biomass burning (HIBB) during early life (which refers to the prenatal period (in-utero) to postnatal period of first six months after birth) is associated with on future health of a girl child, measured by her adolescent height (in cm). Formally, we estimate the following empirical model:

$$H_{icsmt} = \beta HIBB_{icsmt} + \theta X_{ics} + \alpha Z_{icsmt} + \gamma_c + \rho_{sm} + \phi_{st} + \varepsilon_{icsmt} \tag{1}$$

$$H_{icsmt} = \delta_1 PrenatalHIBB_{icsmt} + \delta_2 PostnatalHIBB_{icsmt} + \theta X_{ics} + \alpha Z_{icsmt} + \gamma_c + \rho_{sm} + \phi_{st} + \varepsilon_{icsmt} \tag{2}$$

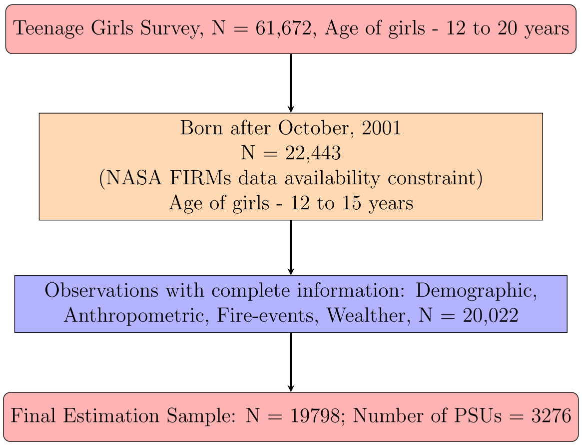

Fig. 3. Sample selection procedure. *Note*: 224 Singleton observations dropped during regression analysis, reducing the final estimation sample to 19,798 observations.

Table 1
Descriptive summary for the estimation sample.

Variable	All		North		South		*t*-test
	Mean	SE	Mean	SE	Mean	SE	
Height (in cm)	149.68	0.06	149.23	0.09	150.42	0.09	$p < 0.01$
Individual &HH characteristics (%)							
Age (in years)	13.71	0.01	13.66	0.01	13.77	0.01	$p < 0.01$
Caste is SCST	0.30	0.00	0.31	0.01	0.29	0.01	$p < 0.01$
Religion is Hindu	0.81	0.00	0.80	0.00	0.83	0.00	$p < 0.01$
HH Size	5.80	0.02	6.19	0.03	5.17	0.03	$p < 0.01$
Rural	0.68	0.00	0.73	0.00	0.60	0.01	$p < 0.01$
Wealth index (%)							
Poorest	0.18	0.00	0.24	0.01	0.10	0.00	$p < 0.01$
Poor	0.19	0.00	0.20	0.01	0.17	0.01	$p < 0.01$
Middle	0.20	0.00	0.18	0.00	0.24	0.01	$p < 0.01$
Rich	0.21	0.00	0.18	0.00	0.28	0.01	$p < 0.01$
Richest	0.21	0.00	0.21	0.00	0.22	0.01	$p < 0.13$
Father's education (%)							
No Education	0.18	0.00	0.20	0.01	0.14	0.00	$p < 0.01$
Class 1 to 5	0.22	0.00	0.21	0.01	0.22	0.01	$p < 0.72$
Class 6 to 11	0.52	0.00	0.50	0.01	0.56	0.01	$p < 0.01$
Class 12 or higher	0.09	0.00	0.09	0.00	0.08	0.00	$p < 0.10$
Mother's education (%)							
No Education	0.33	0.00	0.40	0.01	0.21	0.01	$p < 0.01$
Class 1 to 5	0.25	0.00	0.25	0.01	0.25	0.01	$p < 0.58$
Class 6 to 11	0.38	0.00	0.31	0.01	0.50	0.01	$p < 0.01$
Class 12 or higher	0.04	0.00	0.03	0.00	0.04	0.00	$p < 0.01$
Mean number of fire-events (75 km radius)							
Early life (parental &postnatal)	148.00	2.79	193.73	4.54	74.28	1.04	$p < 0.01$
Prenatal	76.41	1.59	99.26	2.57	39.58	0.66	$p < 0.01$
Postnatal	71.59	1.54	94.47	2.49	34.69	0.70	$p < 0.01$
Observations	19,798		12,944		6854		

Source: Teenage Girl's Survey, 2016–17.

Our main outcome of interest (H_{icsmt}) is height of a surveyed teenage girl i who resides in PSU (village or enumeration block) c and was born in month m and year t in state s. The main variable of interest is a dummy variable $HIBB_{icsmt}$ which captures high intensity biomass burning in the 75 km radius circle around the PSU location during the early life period for a girl. This variable is constructed by creating 20 quantiles for a variable which captures exposure to total number of probability weighted fire-events in early life in the 75 km radius circle around a PSU location. All observations which lie to the extreme right of the distribution or 20th quantile (or top 5% of the sample) of the sample were coded as HIBB with value 1, while all other observations from 1st to 19th quantile were coded as HIBB equal to 0. Thus, HIBB refers to extreme right tail (top 5%) of the distribution of total number of fire-events experienced during early life by girls in our sample. In Eq. (2), we divide early life exposure into two components – prenatal and postnatal period. The variables $PrenatalHIBB_{cmt}$

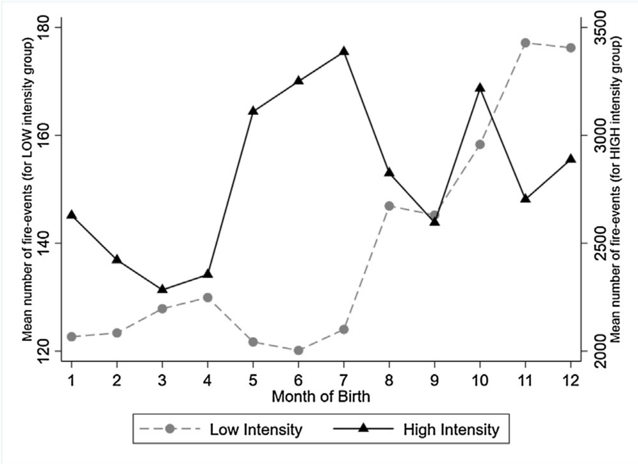

Fig. 4. Mean fire-events during early life (total exposure during nine months of prenatal & six months of postnatal period) by month of birth for high and low intensity groups. Y-axis on the left represents mean fire-count values for the low intensity group (HIBB=0) and Y-axis on the right is for the high intensity group (HIBB=1).

and $PostnatalHIBB_{cmt}$ are dummy variables which have been constructed in a similar manner as before. For example, the variable $PrenatalHIBB_{cmt}$ is constructed by dividing the distribution of total number of fire events for the prenatal period into 20 quantiles, with observations for individuals which belong to the highest (20th) quantile taking value 1 and 0 for all other individuals belonging to 1st to 19th quantile.[10]

We control for confounding factors in the vector X_{ics} which includes age of the girl, religion, caste, household size, dummy for girl defecating in the open (open defecation practice has been found to be associated with height outcomes (Spears et al., 2013)) and wealth category of her household. Additionally, it includes mother's and father's educational background. Other confounding factors include rainfall and temperature which are accounted in our model by introduction of the vector Z_{icsmt}. One of the limitation of our study is that we are not able to capture the *genetic* factors associated with height of an offspring as TAG dataset does not collect anthropometric information for parents. However the wealth category which is included in our analysis is found to be strongly associated with height of an adult, so it can be interpreted as a proxy for better (height wise) genetically endowed parents.[11]

Different regions can have different levels of development (health infrastructure, altitude) which can affect health of an individual hence we include PSU fixed effects (γ_c) in our specification to account for village level time invariant characteristics. PSU fixed effects accounts for mean exposure levels for all girls within the same PSU. Alternatively put, the PSU fixed effects capture the mean exposure to fire events for each PSU, i.e. it accounts for the fact that some areas generally have exposure levels which are higher in comparison to other areas. We also include state-month of birth specific fixed effects to capture seasonality patterns within a state (ρ_{sm}). Inclusion of state-year of birth fixed effects (ϕ_{st}) help us to account for the effect of being born in a particular state and in a particular year (any state level yearly shocks like change in health policy for a state in a particular year will be captured by these fixed effects). We thus exploit spatial variation within a state (comparing girls born in same month or year within a state but in different villages) and temporal variation within a village (comparing girls who reside in same village but belong to different birth cohorts).

6. Results

We first provide some descriptive results, in Fig. 4, we show how exposure to fire-events is different for the two groups (High Intensity group with HIBB = 1 versus Low Intensity group with HIBB = 0). We plot the average number of total fire-events experienced during early life (prenatal + postnatal) by month of birth for high and low intensity group. We observe that there is temporal variation based on the month of birth. Additionally, we observe that the difference in level of exposure to fire-events is quite substantial for these two groups. Next, we plot mean height for girls for the two groups (high intensity exposure group, HIBB = 1 and low intensity exposure group, HIBB = 0) by their wealth category (Fig. 5). We observe that the height for the high exposure group is lower than the height for the low exposure group for almost all wealth categories (except for the richest wealth category where the girls from high exposure group seem to be doing better than girls from

[10] The cut-off for total number of fire-events for which HIBB variable takes value 1 is 1503, for $Prenatal_{HIBB}$ the cut-off is 690 and for $Postnatal_{HIBB}$ the cut-off is 657.

[11] National Family Health Survey (2015–16) is a pan-India health survey which captured height of mothers. Appendix Table A2 shows that Richest wealth category has the highest height in comparison to Poorest wealth category for women in India.

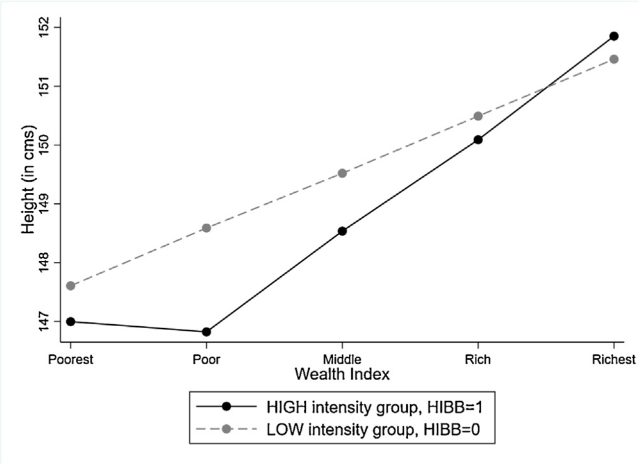

Fig. 5. Mean height by wealth groups for high intensity exposure group (HIBB = 1) and low intensity exposure group (HIBB = 0).

Table 2
High intensity biomass burning and adolescent height.

	(1)	(2)
High Intensity Biomass Burning (HIBB)	−1.070*	
	(0.648)	
Prenatal: HIBB		−1.696**
		(0.708)
Postnatal: HIBB		−1.486**
		(0.598)
Observations	19,798	19,798
Mean Height (in cm)	149.68	149.68
Individual &HH controls	√	√
Weather controls	√	√
Fixed effects		
PSU	√	√
State*Year of Birth	√	√
State*Month of Birth	√	√
R^2	0.38	0.38

Note: Standard errors are clustered at PSU level. Observations are weighted using sample weights. Notation for *p*-values *** is $p < 0.01$, ** is $p < 0.05$ & * is $p < 0.1$. Regressions include controls for age of girl, religion, caste, household size, open defecation, wealth index, education level of mother and father. Weather controls for rainfall and temperature also included.

low exposure group, perhaps because of better resources available with the richest households which they can use to abate any harmful health effects).

6.1. High intensity biomass burning and teenage height

We begin by presenting our result on effect of exposure to high levels biomass burning during early life on teenage height in Table 2. We observe that girls who experienced high intensity biomass burning (HIBB) have shorter height by 1.07 cm. When we split the exposure to biomass burning into prenatal and postnatal exposure (Column 2 in Table 2), then we observe that HIBB during both prenatal and postnatal period affect height of a teenage girl. Exposure to high levels of biomass burning during prenatal period is associated with a decrease in height by 1.70 cm (or 1.13 percent) and for postnatal period the effect on adolescent height is −1.49 cm (or a decrease in height by 0.99 percent).

Moving to other covariates (results reported in Appendix Table A3), we find that height of teenage girls in our sample is similar for different ages (ages 12 to 15). Girls from marginalized caste groups are found to be shorter in comparison to girls from non-marginalized caste group (significant at 10 percent level, Table A3 column 2) and household size is found to be negatively correlated to adolescent height but the effect is statistically insignificant. Literature has found open defecation practice in the neighbourhood to be negatively associated with stunting (height for age) measures, however in our sample although the effect of contemporaneous open defecation practice by a girl is negative but it is found to be insignificant.

We also observe that higher wealth status is associated with taller height for teenage girls. Education level of a mother is also found to be strongly associated with height, with more educated mothers having taller daughters (Some positive association is also observed for father's educational background and height of daughters. Highly educated fathers in our

Table 3
Sensitivity analysis.

	Alternate radius 100 km		Alternate cutoff for HIBB		Alternate pregnancy duration			
					38 weeks		35 weeks	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HIBB	−1.260*		−1.091		−1.070*		−1.080*	
	(0.669)		(0.676)		(0.647)		(0.633)	
Prenatal: HIBB		−1.746***		−1.332**		−1.696**		−1.374**
		(0.662)		(0.618)		(0.707)		(0.637)
Postnatal: HIBB		−1.201**		−1.080**		−1.487**		−0.946*
		(0.487)		(0.538)		(0.598)		(0.539)
Observations	19,798	19,798	19,798	19,798	19,798	19,798	19,798	19,798
Mean Height	149.68	149.68	149.68	149.68	149.68	149.68	149.68	149.68
Individual &HH controls	√	√	√	√	√	√	√	√
Weather controls	√	√	√	√	√	√	√	√
Fixed effects								
PSU	√	√	√	√	√	√	√	√
State*Year of Birth	√	√	√	√	√	√	√	√
State*Month of Birth	√	√	√	√	√	√	√	√

Note: Standard errors are clustered at PSU level. Observations are weighted using sample weights. Notation for p-values *** is $p < 0.01$, ** is $p < 0.05$ & * is $p < 0.1$. Regressions include controls as mentioned in notes for Table 2.
Alternate cut-off for HIBB (High Intensity Biomass Burning) refers to a dummy variable for exposure to high intensity biomass burning. The distribution of fire-events is divided into 15 quantiles with observations belonging to the highest quantile (15th) being coded as 1 and observations belonging to 1st to 14th quantile were coded as 0.
Alternate pregnancy durations are taken as 38 and 35 weeks (shorter gestational age in comparison to the original gestational age).

sample i.e. fathers with education above class 12, have taller daughters in comparison to fathers with low levels of education). These results suggest that wealthier families and households with highly educated parents are perhaps able to direct more resources for betterment of health of their children.

6.2. *Sensitivity analysis*

6.2.1. *Alternate radius of analysis*

We have provided our main results with radius of analysis as 75 km, we now change this radius to an alternate larger radius of 100 km to check whether our results our sensitive to the choice of radius. In Table 3 (columns 1 and 2) we re-establish our main results with the new radius and find that our results remain unchanged i.e. they have similar magnitude as before.

6.2.2. *Alternate cut-off for high intensity biomass burning exposure*

Our key explanatory variables related to exposure to biomass burning (*HIBB*, *PrenatalHIBB* and *PostnatalHIBB*), had originally been constructed by creating 20 quantiles for the total number of fire-events in the local area during the prenatal or postnatal period. All observations which lie to the extreme right of the distribution or 20th quantile (or top 5% of the sample) of the sample were coded as HIBB with value 1, while all other observations from 1st to 19th quantile had HIBB value as 0. As a sensitivity check, we alternatively split the data on exposure to fire-events into 15 quantiles and code top most quantile (15th quantile) as HIBB with value 1 and 0 otherwise. In columns 3 and 4 of Table 3, we observe that even after following this new definition for exposure variables our results are similar to our original results in Table 2.

We also provide analysis for multiple other absolute cut-off values which are used to construct the HIBB variable. In Fig. 6, we plot estimated beta coefficients (with 90 percent CI) for different models which use different cut-off values to construct the HIBB variable. As depicted in the graph, almost all of the estimated coefficients are negative. For lower exposure cut-offs (cut-off values less than 700 fire-events) the effect is not significant. For higher cut-off values most of the beta coefficients are significant at 10 percent level. We choose a higher cut-off value to depict extreme exposure to biomass burning. In our main analysis (Table 2) the cut-off value chosen for HIBB variable construction is 1503 which corresponds to the 20th quantile of the fire distribution but as shown by the graph below our results are robust to other alternate cut-off values as well.

6.2.3. *Alternate pregnancy duration*

We calculate retrospective exposure to biomass burning (prenatal period) using an average gestational period of 9 months (≈39 weeks). However there can be concerns about gestational age being shorter than the assumed period of 9 months due to exposure to biomass burning. Rangel and Vogl (2019) find that gestational age reduces due to exposure to pollution. We re-create our main results (Column 5 to 8, Table 3) by using shorter gestational periods of 38 weeks and 35 weeks. We find that our estimates are not sensitive to a specific choice of gestational age.

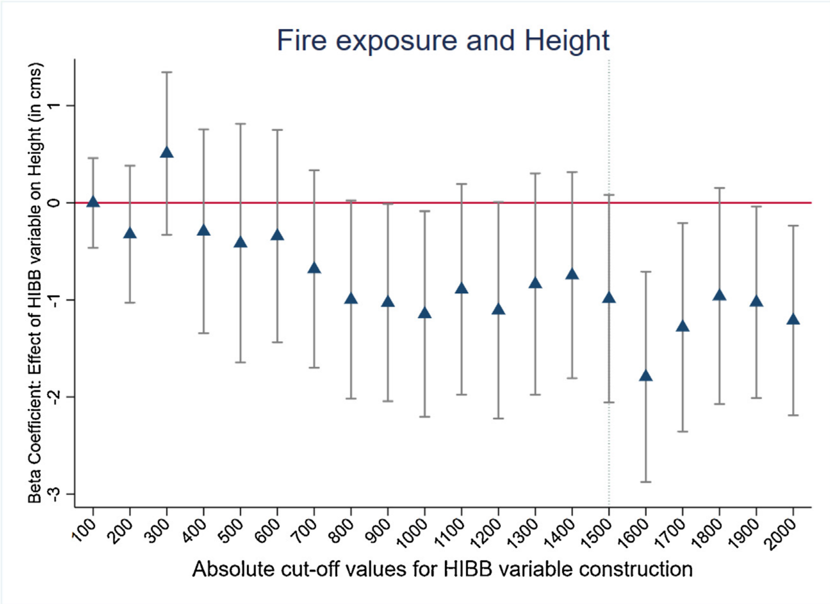

Fig. 6. Coefficients for regression (with 90% CI) of height (in cm) for different HIBB variables which are constructed by using different cut-off values. Each coefficient depicts a separate regression. Regressions include controls for age of girl, religion, caste, household size, open defecation, wealth index, education of mother and father. Weather controls for rainfall and temperature also included. Fixed effects included are same as the ones mentioned in Table 2.

6.3. *Socio-economic status (SES) for high and low intensity groups*

One of the important confounding factor in our analysis is the socio-economic (SES) background of teenage girls. Literature suggests that a disproportionate burden of stunting is observed among the children from poor SES (Kanjilal et al., 2010), thus one of the threats to our methodology is the fact that our results might be completely driven by low SES for the high intensity burning (HIBB = 1) group. To eliminate the possibility of our results being primarily driven by SES variables, we check if there is systematic relationship between various SES variables and our main independent variables (i.e. HIBB, Prenatal HIBB and Postnatal HIBB). We present these results in Table 4 for several SES variables: Wealth Index, access to electricity, educational background of mother and father; and few variables which act as a proxy for SES of a household – household size and practice of open defecation (poorer households tend to be larger in size and households which belong to hindu religion are more likely to practice open defecation (Geruso and Spears, 2018)). We observe that none of these variables are systematically associated with our key independent variables, hence we can claim that the results are not driven by differences in SES between the two groups.

6.4. *Robustness checks*

6.4.1. *Different fixed effects*

As part of robustness check we now show that our results hold up for different specifications. Columns 1 to 12 in Table 5 introduce different combinations of fixed effects which have been used for analysis (while columns 11 and 12 contains our original results with full set of controls). In column 1, no controls have been introduced except PSU fixed effects and we find that HIBB is associated with a decrease in height by −2.42 cm. Moving from column 1 to 3, we control for seasonality in the data by introducing dummies for different months and we observe that our estimate is still close to −2.5 cm. We refine this specification further by controlling for region specific seasonality (column 5, Table 5) by introducing state by month fixed effects. Our estimate still remains significant and the magnitude increases to −2.73 cm. Next, we account for yearly shocks (columns 7 and 9, Table 5) and observe that the magnitude of β (coefficient for HIBB variable) reduces substantially and it is close to our original estimate. Similarly, we observe strong negative association between high intensity biomass burning during prenatal (and postnatal) period and adolescent height for different combinations of fixed effects (columns 2, 4, 6, 8 and 10). We find that estimates for these alternate specifications lead to very similar estimates when compared with our original results.

6.4.2. *Other robustness checks*

6.4.2.1. Fires with brightness measure. We now provide additional multiple robustness checks for our analysis. We begin by providing results for an alternate measure of fire exposure where fire exposure variables were constructed by using their brightness. In Table 6 (Columns 1 and 2) we replicate our original results by using HIBB, prenatal HIBB and postnatal HIBB

Table 4
Sensitivity analysis – SES variables.

	OD		Wealth index		Electricity	
	(1)	(2)	(3)	(4)	(5)	(6)
HIBB	−0.009 (0.024)		−0.030 (0.089)		−0.039 (0.026)	
Prenatal: HIBB		−0.021 (0.019)		0.062 (0.078)		−0.012 (0.016)
Postnatal: HIBB		0.018 (0.023)		0.038 (0.080)		−0.024 (0.017)
Observations	19,798	19,798	19,798	19,798	19,798	19,798
Individual &HH controls	√	√	√	√	√	√
Weather controls	√	√	√	√	√	√
Fixed effects						
PSU	√	√	√	√	√	√
State*Year of Birth	√	√	√	√	√	√
State*Month of Birth	√	√	√	√	√	√
	Father's education		Mother's education		HH size	
	(7)	(8)	(9)	(10)	(11)	(12)
HIBB	0.031 (0.042)		−0.052 (0.048)		0.020 (0.157)	
Prenatal: HIBB		−0.026 (0.040)		−0.020 (0.045)		0.069 (0.141)
Postnatal: HIBB		0.037 (0.043)		0.020 (0.046)		−0.003 (0.117)
Observations	19,798	19,798	19,798	19,798	19,798	19,798
Individual &HH controls	√	√	√	√	√	√
Weather controls	√	√	√	√	√	√
Fixed effects						
PSU	√	√	√	√	√	√
State*Year of Birth	√	√	√	√	√	√
State*Month of Birth	√	√	√	√	√	√

Note: Standard errors are clustered at PSU level. Observations are weighted using sample weights. Notation for p-values *** is $p < 0.01$, ** is $p < 0.05$ & * is $p < 0.1$. Regressions include controls as mentioned in notes for Table 2.

variables constructed by using brightness weighted fire exposure for girls in our sample. We observe that our estimates are slightly smaller in magnitude in comparison to our original results but they are still negative and significant[12] .

6.4.2.2. Dose effect. We now estimate a dose response function for the relationship between adolescent height and exposure to fire-events during early life (prenatal and postnatal combined). We construct five bins for exposure to total number of fire-events: 0 to 499, 500 to 999, 1000 to 1499, 1500 to 1999 and above 2000.[13] Estimating Eq. (1) by replacing dummy variable HIBB with these 4 categories for fire-exposure (1 category i.e. 0 to 499 is chosen as base category) reveals that as exposure to fire-events increases adolescent height decreases (Fig. 7 and Table 6, column 3). The estimates for all bins are negative, with estimate for the 2000+ category (extremely high level of biomass burning) being particularly huge i.e. −2.83 cm, that is girls who experienced more than 2000 fire-events during their early life are found to be shorter by 2.83 cm in comparison to girls who experienced 0 to 499 fire events during their early life. Estimates for categories: 1000 to 1499 and 1500 to 1999 are also negative but significant only at 13 and 11 percent respectively.

6.4.2.3. Difference-in-difference estimate. We also adopt a simple difference-in-difference strategy to assess the association between exposure to fire-events and height of girls. We conduct this analysis by first identifying *high burning states*. This is done by using data from Appendix Table A1 which contains fire burning patterns[14] for each state in each month for time period 2001 to 2005. The high burning states (we interpret them as "treatment" states) are the ones for which the cells are highlighted in appendix Table A1, these are the top 10 percent observations in terms of fire activity in this table. Next, we identify *high risk conception months* for each of the high burning states – i.e. these are months for which more than 4 periods (or months) are high burning months out of a total of 15 months of early life (Appendix Table C1). To elaborate this further

[12] The coefficient on HIBB variable is found to be significant at 13 percent level.
[13] As shown by number of observations in each bin it is evident that our exposure variable is highly skewed which is the reason for using threshold analysis throughout this paper.
[14] The figures in Appendix Table A1 are mean of total fire events which occur in a state in each month. The average is calculated for 5 years – 2001 to 2005.

Table 5
Robustness checks – different fixed effects.

	No covariates & PSU FE		No covariates, PSU FE & general seasonality		No covariates, PSU FE & regional seasonality	
	(1)	(2)	(3)	(4)	(5)	(6)
HIBB	−2.421***		−2.498***		−2.735***	
	(0.478)		(0.482)		(0.519)	
Prenatal: HIBB		−2.586***		−2.638***		−2.661***
		(0.501)		(0.505)		(0.564)
Postnatal: HIBB		−1.653***		−1.695***		−2.396***
		(0.428)		(0.433)		(0.537)
Observations	19,798	19,798	19,798	19,798	19,798	19,798
Individual &HH controls						
Weather controls						
Fixed effects						
PSU	√	√	√	√	√	√
Month of Birth			√	√		
State*Year of Birth						
State*Month of Birth					√	√

	No covariates, PSU FE & regional yearly shocks		No covariates, PSU FE, regional seasonality & regional yearly shocks		Covariates, PSU FE, regional seasonality & regional yearly shocks	
	(7)	(8)	(9)	(10)	(11)	(12)
HIBB	−1.124*		−1.020		−1.070*	
	(0.573)		(0.653)		(0.648)	
Prenatal: HIBB		−1.733***		−1.668**		−1.696**
		(0.596)		(0.705)		(0.708)
Postnatal: HIBB		−0.870*		−1.333**		−1.486**
		(0.487)		(0.613)		(0.598)
Observations	19,798	19,798	19,798	19,798	19,798	19,798
Individual &HH controls					√	√
Weather controls					√	√
Fixed effects						
PSU	√	√	√	√	√	√
Month of Birth						
State*Year of Birth	√	√	√	√	√	√
State*Month of Birth			√	√	√	√

Note: Standard errors are clustered at PSU level. Observations are weighted using sample weights. Notation for *p*-values *** is $p < 0.01$, ** is $p < 0.05$ & * is $p < 0.1$. Regressions include controls as mentioned in notes for Table 2.

we provide an example by using state of Assam. Table A1 identifies that the months of March and April as high burning months for the state of Assam. Now suppose a girl is conceived in the month of January (first column of Table C2) then she experiences 3 months of high burning exposure during her early life; while if she is conceived in the month of February then she experiences 4 months of high burning exposure and so on. This is represented in the last row of Table C2 which provides number of periods or months of high burning exposure by each conception month (this same as the row for state of Assam in Table C1).

To formalize our DID estimation, for each girl in our sample we use a dummy variable (HighBurning*HighRisk) which takes value 1 if she belongs to a high burning state and if she is conceived in a high risk conception month (i.e. she has more than 4 periods of high exposure to biomass burning during her early life). Other control variables remain same as our original estimation exercise. We provide the DID estimation result in column 4 of Table 6 and find that a girl who belongs to a high burning state and conceived in a high risk conception month is shorter by 0.4 cm (this estimate is significant at 13 percent level). This DID estimate is an effect on the extensive margin as we do not use the extent of actual fire burning experienced by the girl in our analysis.

6.4.2.4. Matching estimate. One of the key concerns about our results can be related to the fact that girls who belong to the high intensity exposure group can have very different characteristics from girls who belong to the low intensity exposure group. The selection based on characteristics can bias the estimates we observe. Thus, we conduct a matching procedure to compare similar girls from the two groups to address any endogeneity issues arising due to selection. We first calculate the probability of being selected into the high intensity exposure group (HIBB = 1) by using observable characteristics of the girls and their households. We then use the pscores obtained to match girls from the treatment group (HIBB = 1) to girls from the

Table 6
Other robustness checks.

	Fires with brightness measure		Bins	Diff-in-Diff	Matching	Continuous measure	Falsification test		Additional exposure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HIBB	−1.001				−1.375**		−0.054		−1.069*	
	(0.660)				(0.631)		(0.585)		(0.647)	
Prenatal: HIBB		−1.359*						0.655		−1.685**
		(0.700)						(0.561)		(0.705)
Postnatal: HIBB		−1.235**						0.260		−1.495**
		(0.591)						(0.624)		(0.602)
Fires between 500–999			−0.379							
			(0.759)							
Fires between 1000–1499			−1.419							
			(0.939)							
Fires between 1500–1999			−1.658							
			(1.054)							
Fires 2000+			−2.834**							
			(1.312)							
HighBurning*HighRisk				−0.396						
				(0.257)						
Fire						−0.131*				
						(0.071)				
Fire*Fire						0.001**				
						(0.001)				
						[p-value = 0.063]				
Fires between month 7 &present									0.002	0.002
									(0.005)	(0.005)
Observations	19,798	19,798	19,798	19,800	5452	19,798	19,798	19,798	19,798	19,798
Individual &HH controls	√	√	√	√	√	√	√	√	√	√
Weather controls	√	√	√	√	√	√	√	√	√	√
Fixed effects										
PSU	√	√	√	√	√	√	√	√	√	√
State*Year of Birth	√	√	√	√	√	√	√	√	√	√
State*Month of Birth	√	√	√		√	√	√	√	√	√
Month of Birth				√						

Note: Standard errors are clustered at PSU level. Observations are weighted using sample weights. Notation for p-values *** is $p < 0.01$, ** is $p < 0.05$ & * is $p < 0.1$. Regressions include controls as mentioned in notes for Table 2.
Fires with brightness measure (column 1 and 2) uses fire-counts which have been weighted by their brightness.
Regression results based on bins (column 3) uses 5 bins of exposure to fire-events where category 0–499 fire-events is used as the base category.
Difference-in-difference estimate (in column 4) is based on the coefficient for HighBurning*HighRisk variable which takes value 1 if a girl belongs to a high burning state (i.e. the state belongs to the 10th decile in terms of exposure to fire-events) and conceived in a month which leads to more than 4 periods (out of total 15 periods in early-life) of intense biomass burning; 0 otherwise.
Matching estimate (column 5) is based on a nearest neighbour matching procedure where HIBB = 1 observations are matched with HIBB = 0 observations by using a caliper value of 0.01. Set of controls used for matching include age dummies, caste category, dummy for religion Hindu, set of dummies for wealth category, set of dummies education of father and mother, dummy for housing type, dummy for rural area, dummy for household with a toilet and dummy for a big household i.e. household with more than 4 members.
Continuous fire measure has been scaled by a factor of 100 (fire variable = fire exposure/100). p-value mentioned in the square brackets reports the joint significance of fire and fire*fire variables in Column 6.
Falsification test (column 7 and 8) moves exposure by 1 year, i.e. the exposure variables no longer correspond to early-life period.

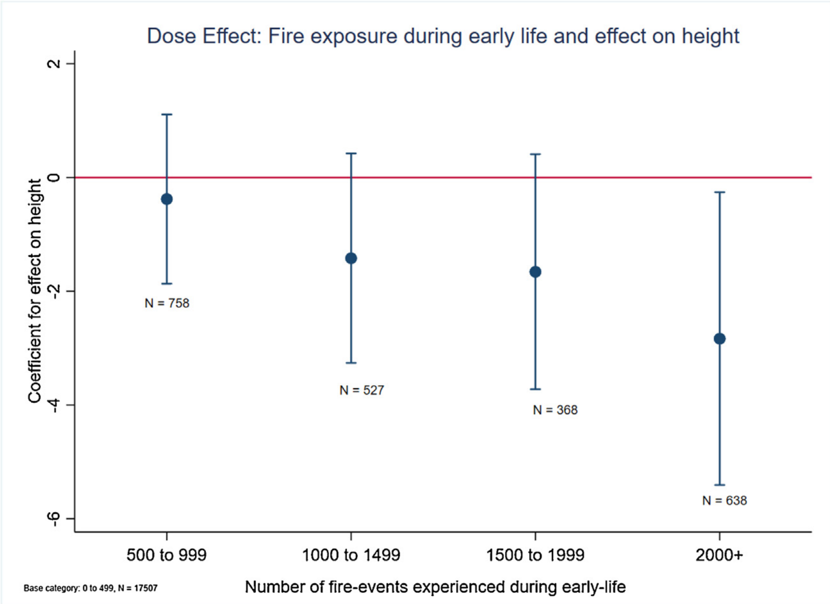

Fig. 7. Coefficients for regression of height (in cm) on 5 bins of fire-exposure. Category 0 to 499 is the omitted category. Regressions include controls for age of girl, religion, caste, household size, open defecation, wealth index, education of mother and father. Weather controls for rainfall and temperature also included. Fixed effects included are same as the ones mentioned in Table 2.

control group (HIBB = 0).[15] We use the nearest neighbour matching procedure[16] and find that the girls who were exposed to extremely high levels of biomass burning during their early life are shorter by 1.37 cm.

6.4.2.5. Continuous variable for fire-exposure. In our analysis we primarily used dichotomous variables to analyze the association between biomass burning and adolescent height. Now we provide our analysis with alternate exposure variable i.e. a continuous measure for exposure to fire events to assess marginal effect of exposure to biomass burning events on height. We observe (in Table 6, column 6) that there is statistically significant quadratic association between fires and height, with diminishing marginal cost of exposure for higher exposure levels. Similar curvature has been observed in the literature where concentration response functions have been estimated (Gupta and Spears, 2017; Pope III et al., 2015).

6.4.2.6. Placebo test. We conduct a randomized inference exercise to test whether the results we observe occurred purely by fluke. We do this by randomizing the HIBB variable (i.e. we shuffle the HIBB status randomly in our sample), this breaks the true relationship between the dependent variable (height) and main independent variable (HIBB). The betas obtained from this randomization depict the results we would have obtained by fluke. If we observe that a lot of these randomized betas take values as high as our estimate then that implies that our true estimate has a high chance of being present purely due to chance rather than an actual true underlying relationship. However, our analysis shows that there is less than 0.01 percent chance of obtaining a replication beta (created by fluke/chance) to be as high as our true estimate (refer Fig. 8: our estimate lies on the extreme left tail of the cumulative distribution function).

Following our analysis, we claim that early life period is of special significance and a shock experienced during this phase (exposure to high intensity biomass burning) can have long term consequences. To test this claim, we move our exposure analysis by an year i.e. instead of analysing the effect of exposure to biomass burning during early life we analyse the effect for exposure experienced over 15 months which starts one year later. In columns 7 and 8, Table 6 we essentially find that exposure variables are no longer significant this is expected as exposure no longer corresponds to the critical phase of development of a child.

6.4.2.7. Exposure beyond early life. Another key concern about our chosen specification can be that biomass burning is a seasonal recurring practice which implies that it occurs not just during the early life period but can be present for later periods as well. Potentially the effects we observe can be due to the exposure experienced beyond early life. To address this

[15] Appendix Table D1 provides the details about the characteristics used for the matching procedure and shows that the two groups are balanced in terms of their mean characteristics values.
[16] We use a caliper value of 0.01 to identify neighbours.

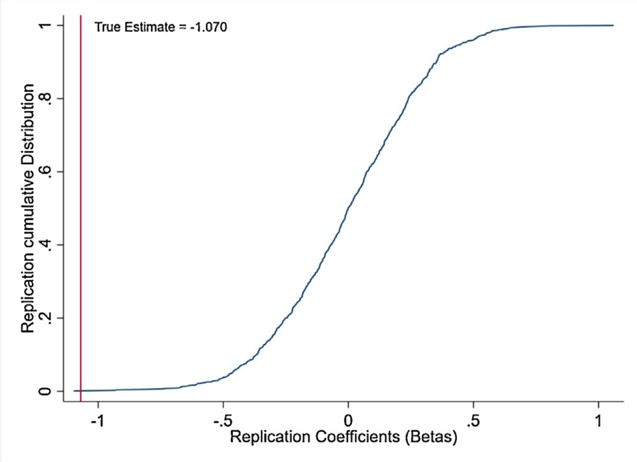

Fig. 8. Placebo Test – Monte Carlo empirical CDF for coefficient β (from Eq. (1)). The CDF plots estimates based on randomized inference obtained after conducting 1000 simulations which randomly assign exposure to high intensity biomass burning status, 1 (HIBB = 1) or 0 (HIBB = 0) to observations. Our result is an extreme value in this set of "coefficients" indicating that it was unlikely to arise due to chance.

concern we additionally control for the level of exposure to biomass burning experienced by girls from month 7 onwards till their present age. We present these results in columns 9 and 10 in Table 6 and find that our estimates remain unchanged.

6.5. Heterogeneity

6.5.1. By region

We now explore the relationship between high intensity biomass burning and adolescent height for different regions of India. This sub-sample analysis is aimed at exploring the tenacity of our results for different regions. Essentially, we want to analyse whether our results hold true for smaller regional blocks which comprise of areas which are known to be relatively high fire activity regions. For example, extremely high levels of biomass burning takes place in North India (Fig. 2) while none of the girls in from South India experience high intensity biomass burning during their early life.

We begin by first limiting our analysis to those states which routinely witness highest levels biomass burning.[17] We find in Table 7 (column 1) that both prenatal and postnatal exposure to high levels of biomass burning is associated with lower adolescent height with effect sizes similar to our original results (in Table 2). Next, we choose three North Indian states (with high levels of biomass burning) and three South Indian states (with low levels of biomass burning) for analysis. We add three southern states to this analysis to further serve as "control" states and in column 2 of Table 7, we find that the effect of HIBB on teenage height is -1.73 cm (for prenatal period) and -1.44 cm (for postnatal period). Finally, we choose all North Indian states and find our estimates are similar to our original results (Table 7, column 3).

North India and High-Burning states are the primary culprits when it comes to imposing a health burden (in terms of reduced adolescent height) due to high fire burning activity. We find that the negative effect of high biomass burning is present in these smaller regional blocks. Since no girl from South India in our sample experiences High Intensity Biomass Burning, and our sub-sample analysis reveals strong negative effects of HIBB during pre-natal and post-natal period for North India and High-Burning states, so we claim that these regions are primarily responsible for reduction in adolescent height due to early-life exposure to high levels of biomass burning.

6.5.2. By age and trimester-wise exposure

The girls in our sample belong to the adolescent age group when they are still growing, we now explore the heterogeneous effect of exposure to HIBB for girls belonging to different age groups. To conduct this analysis we interact our age dummies with the dummy for high intensity biomass burning. These interactive variables essentially capture the differential effect of HIBB for girls from different age groups. Our results are presented in Table 8 (column), we observe that the coefficient on these interactive variables is negative for all age groups but mostly significant for girls who are 14 years old.

Lastly, we provide heterogeneous effects for different phases of development. We divide the early life period of 15 months (9 months prenatal + 6 months postnatal) into 5 phases of 3 months each. We use a continuous measure for fire exposure for each of these phases and provide the results for this analysis in column 2 of Table 8. The betas for each of these exposure

[17] These states are Andhra Pradesh, Arunanchal Pradesh, Assam, Chhattisgarh, Haryana, Karnataka, Madhya Pradesh, Maharashtra, Manipur, Meghalaya, Mizoram, Nagaland, Odisha, Punjab, Tripura, Uttar Pradesh and Uttarakhand. All observations in Appendix Table A1, are arranged in ascending order based on mean total fires for each month for the period 2001–2005. The top 10 percent of these observations are selected as high burning observations. The list of states mentioned above are the ones which appear in this list of top 10 percent observations in terms of occurrence of fire events.

Table 7
Region wise analysis.

	(1) High intensity burning states	(2) North India: Punjab, Haryana, Assam & South India: Kerala, AP, Tamil Nadu	(3) North India
Prenatal: HIBB	−1.675**	−1.730**	−1.676**
	(0.719)	(0.789)	(0.709)
Postnatal: HIBB	−1.435**	−1.436**	−1.326**
	(0.613)	(0.690)	(0.610)
Observations	4473	4610	12,944
Individual &HH controls	√	√	√
Weather controls	√	√	√
Fixed effects			
PSU	√	√	√
State*Year of Birth	√	√	√
State*Month of Birth	√	√	√

Note: Standard errors are clustered at PSU level. Observations are weighted using sample weights. Notation for p-values *** is $p < 0.01$, ** is $p < 0.05$ & * is $p < 0.1$. Regressions include controls for age of girl, religion, caste, household size, open defecation, wealth index, education level of mother and father. Weather controls for rainfall and temperature also included.
High Intensity Burning States (see Appendix Table A1, highlighted cells depict state-month combinations with highest burning) include Andhra Pradesh, Arunanchal Pradesh, Assam, Chhattisgarh Haryana, Karnataka, Madhya Pradesh, Maharashtra, Manipur, Meghalaya, Mizoram, Nagaland, Odisha, Punjab, Tripura, Uttar Pradesh and Uttarakhand.
North Indian States include Arunachal Pradesh, Assam, Bihar, Gujarat, Haryana, Himachal Pradesh, Jammu and Kashmir, Jharkhand, Madhya Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, New Delhi, Punjab, Rajasthan, Sikkim, Tripura, Uttar Pradesh, Uttarakhand and West Bengal.

Table 8
Age-wise & trimester-wise results.

	(1)	(2)
Age 12–13 * HIBB	−1.038	
	(0.923)	
Age 14 * HIBB	−1.162*	
	(0.664)	
Age 15 * HIBB	−0.835	
	(1.024)	
Trimester-1 Fire Count		−0.068
		(0.048)
Trimester-2 Fire Count		−0.063
		(0.061)
Trimester-3 Fire Count		−0.100**
		(0.049)
		[$p_1 = 0.063$]
Postnatal 1–3 months Fire Count		−0.075
		(0.046)
Postnatal 4–6 months Fire Count		0.056
		(0.051)
		[$p_2 = 0.81$]
		[p_3 (for all 5 phases) = 0.14]
Observations	19,798	19,798
Individual &HH controls	√	√
Weather controls	√	√
Fixed effects	√	√
PSU	√	√
State*Year of Birth	√	√
State*Month of Birth	√	√

Note: Standard errors are clustered at PSU level. Observations are weighted using sample weights. Notation for p-values *** is $p < 0.01$, ** is $p < 0.05$ & * is $p < 0.1$. Regressions include controls as mentioned in notes for Table 2. Fire measures have been scaled by a factor of 100. The terms in square brackets provide the p-values for joint significance tests. p_1 refers to joint significance for trimester 1, 2 and 3 fire-exposure; p_2 refers to joint significance for post-natal exposure during first 3 months after birth and for 4–6 months after birth; p_3 provides p-value for joint significance test for variables corresponding to exposure during all 5 phases i.e. 3 months durations starting from trimester 1 till 6 months after birth.

windows capture the effect of exposure to biomass burning events and adolescent height. We observe that most of the betas are negative, with the effect for third trimester and first three after birth being significant as well. An increase in fire-events by 100 units during third trimester is associated with a decrease in height by 0.1 cm and a similar increase in exposure during first three months is associated with an decrease in height by 0.075 cm. We provide joint significance tests for complete

Table 9
Non-pollution mechanisms: using NSS 2004–05.

	(1) Labor SS	(2) Med Exp	(3) MPCE	(4) Cereals	(5) Pulses	(6) Milk	(7) Meat	(8) Veg	(9) Fruits
Fire	−0.009** (0.004)	0.055** (0.028)	−0.002 (0.003)	−0.006* (0.004)	0.001 (0.004)	−0.014*** (0.004)	0.002 (0.007)	−0.005 (0.004)	−0.005 (0.007)
Observations	123,657	123,562	123,682	121,424	119,491	98,860	78,662	121,266	98,427
HH controls	√	√	√	√	√	√	√	√	√
Fixed effects									
District	√	√	√	√	√	√	√	√	√
State*Month	√	√	√	√	√	√	√	√	√
State*Year	√	√	√	√	√	√	√	√	√

Note: Standard errors are clustered at District level. Notation for p-values *** is $p < 0.01$, ** is $p < 0.05$ & * is $p < 0.1$. Dependent variables have been mentioned in the column heads, all dependent variables are log transformed values. Fire variable has been scaled by a factor of 100. Regressions include household level controls which include a dichotomous control for sector being rural, dummy for a big household with number of members > 6, religion of the household (Hindu, Islam and Others), social group (General, Schedule Caste, Schedule Tribe and Others) and a dummy for household being a rural agricultural household. Regressions in columns 4 to 9 capture the intensive margin effects i.e. these regressions only capture those households who reported a positive expenditure on food items (cereals, pulses, milk, meat, vegetables and fruits).

prenatal, postnatal and early life (all five phases taken together) period as well and find that they are significant for prenatal period (p-value = 0.064).[18]

6.6. Mechanism

We now explore the mechanisms which might explain the results we observed. To explore these mechanisms, we use a nationally representative pan-India survey – the 61st round for National Sample Survey (NSS). This survey captured over 120,000 households across all major states in India, for our analysis we use the consumption survey and employment-unemployment survey. The survey was conducted in 2004–2005, this is the time-period which is closest to our main analysis (which focuses on early life of adolescent girls during 2001 till 2005).

The NSS data records retrospective information on many other variables which are helpful for exploring the underlying mechanisms like food availability, labor supply, consumption patterns, etc. We combined the NSS data with fire-events dataset (FIRMS) by using district and survey date of the household and created a lagged exposure variable. Our main exposure variable is the total count of probability weighted fire-events in the 60 days duration before the interview date for a household (the 60 days duration captures the delayed effect of exposure on our dependent variables). Following TanSoo and Pattanayak, 2019 we explore the non-pollution mechanisms by looking at the relationship between labor supply, medical expenditure, consumption expenditure on food items and exposure to fire-events. In our analysis, we use log transformed variables for total labor supply for a household (during last 7 days), total medical expenditure (during last 30 days), total monthly consumption expenditure (during last 30 days), total consumption value for food items like cereals, pulses, milk, meat, vegetables and fruits as dependent variables. Additionally, in our analysis we introduce district fixed effects to capture time-invariant characteristics at the district level, state-month fixed effects to capture state level seasonality and state-year fixed effects to account for state-level yearly shocks. We also control for household characteristics like dummy for a large household, religion, sector (rural or urban), social background (caste categories) and a dummy for household being a rural agricultural household.

We present our results from this analysis in Table 9. In column 1, we explore the labor market effects of exposure to biomass burning. We used a lagged exposure variable to capture the delayed impact of exposure to biomass burning on health of household members due to which they themselves may not be able to work or they may not be able to work to provide care giving to a household member who falls sick. We find that there is a negative and significant correlation between the amount of labor supplied and exposure to fire-events. A 100 unit increase in fire exposure is associated with a decrease in labor supply by 0.9 percent. Other studies which have explored the relationship between pollution and labor supply also report a similar negative relationship (Aragón et al., 2016; Holub et al., 2020; Montt, 2018; Kim et al., 2017; Borgschulte et al., 2018). We also find (in Column 2) that non-institutional medical expenditure has a positive and significant association with exposure to fire-events[19] which suggests plausible health channels via which biomass burning might directly affect health of a mother or health of primary wage earner in the household or other household members. These results are in line with the literature which has established adverse short-term effects of exposure to fire-events on respiratory and cardiovascular health (Chakrabarti et al., 2019; Singh et al., 2021).

The reduction in labor supply can potentially have an effect on the resources available for a pregnant mother or a young child within household. We next explore the consumption patterns for the household, in columns 3 to 9 of Table 9. We

[18] The p-value for the joint significance for all five phases taken together is 0.145.
[19] We find no significant association between institutional medical expenditure and exposure to biomass burning.

observe that the effect of exposure to biomass burning on total monthly consumption expenditure (MPCE, in column 3) is insignificant while it is negative and significant on two important food items in Indian diet – cereals and milk.

Overall, our analysis suggests that exposure to biomass burning is associated with reduced labor supply, increased medical expenditure and reduced consumption of few food items. Lastly, in Appendix we explore, the direct relationship between pollution (PM2.5) and biomass burning. We find a strong positive relationship between air pollution and fire-events.

7. Conclusion

Our analysis shows that high intensity biomass burning is associated with lower adolescent height for teenage girls in India. We find that girls who were exposed to extremely high levels of biomass burning during their early life have lower height by -1.07 cm or a decrease of 0.7 percent. This association is driven by exposure to high intensity biomass burning during both the prenatal period and postnatal period. The underlying non-pollution mechanisms at play suggest reduced labor supply, reduced consumption of food items like milk and cereals and increased sickness in the households as revelaed by higher medical expenditures in response to an increase in fire-activity. North Indian states are most vulnerable as high intensity biomass burning primarily occurs in this region. Among the North Indian states few states stand out on account of high levels of biomass burning, these include Punjab, Haryana, Assam, Manipur, Mizoram, Meghalaya, Madhya Pradesh, Tripura and Nagaland. We find that even for this smaller subset of states the occurrence of high intensity biomass burning is strongly correlated with shorter adolescent height.

Height of an individual is an important health outcome to focus on as it is associated with cognition level, future earnings, educational attainment and future disease vulnerability (Almond and Currie, 2011; Victora et al., 2008). Reductions in biomass burning levels can potentially have many positive outcomes related to girls studying further, earning more and having better health profile in future. 66% of workforce in India is found to be stunted, eliminating stunting can increase GDP by 10% (mean estimate for increase in GDP from Galasso et al. (2016) for South Asian countries), gains in height associated with reduction in biomass burning can also contribute to an increase in GDP of the nation.

India needs effective policies regarding regulation and management of biomass burning. Fire suppression strategies are needed; however, the budget allocation for this purpose is really small and remains unused in every financial year. Similarly the government has committed itself to subsidising the use of happy-seeder technology (this is an alternative to combine harvester, it leaves rice residue in form of a mulch on farm which does not hamper wheat crop sowing and hence does not require burning), however the uptake of this policy remains quite low due to high initial investment in the machine (Shyamsundar et al., 2019; Gupta, 2014). Under a new scheme government has allocated 1150 crore ($125 Million) rupees for curbing crop burning in 4 north Indian 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.[20] Such multi-pronged policies are needed urgently to address both short term and long term negative outcomes associated with biomass burning.

Author statement

Prachi Singh: Conceptualization, Methodology, Formal Analysis, Data Curation, Writing – Original Draft, Writing – Review and Editing, Visualization, Project administration.

Sagnik Dey: Data Curation, Resources, Writing – Review and Editing.

Conflict of interest

The authors declare no conflict of interest.

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Appendix A

[20] Source: MoAFW (Ministry of Agriculture and Farmers' Welfare), Government of India Report of the committee on the review of the scheme "Promotion of agricultural mechanisation for in-situ management of crop residue in states of Punjab, Haryana, Uttar Pradesh and NCT of Delhi". Available from: https://farmech.dac.gov.in.

Table A1
State-wise mean fire-events for each month for time-period 2001–2005.

State	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Andaman & Nicobar Island	0	0	1	0	0	1	1	0	0	0	0	0
Andhra Pradesh	104	328	506	111	69	10	4	2	13	11	19	46
Arunanchal Pradesh	113	87	161	111	100	29	4	1	3	17	20	61
Assam	79	132	585	431	32	4	1	3	9	19	46	79
Bihar	7	22	46	57	8	4	1	1	1	2	9	40
Chandigarh	0	0	0	0	0	0	0	0	0	0	0	0
Chhattisgarh	16	53	307	266	117	8	1	2	10	9	8	11
Dadara & Nagar Havelli	0	1	0	0	0	0	0	0	0	0	0	0
Daman & Diu	0	0	0	0	0	0	0	0	0	0	0	0
Goa	1	0	1	1	1	0	0	0	0	0	1	3
Gujarat	53	52	132	82	27	8	2	2	3	12	29	45
Haryana	14	27	16	207	368	4	1	2	6	473	114	41
Himachal Pradesh	18	5	6	11	59	34	1	0	0	1	10	18
Jammu & Kashmir	6	9	6	15	52	44	1	0	1	3	19	9
Jharkhand	23	25	85	84	34	7	6	6	18	27	40	32
Karnataka	104	248	225	29	15	3	0	1	2	7	23	82
Kerala	16	75	68	5	1	0	0	0	1	0	0	4
Lakshadweep	0	0	0	0	0	0	0	0	0	0	0	0
Madhya Pradesh	43	68	398	585	143	19	4	4	7	15	48	43
Maharashtra	150	204	561	287	107	13	1	0	5	9	51	142
Manipur	41	172	795	470	25	1	0	0	0	1	3	9
Meghalaya	21	58	665	146	5	0	0	0	0	0	4	16
Mizoram	8	165	1953	546	8	0	0	0	0	0	1	1
NCT of Delhi	0	0	0	1	2	0	0	0	0	0	1	0
Nagaland	121	192	627	124	4	0	0	0	0	1	5	59
Odisha	17	117	532	316	169	15	2	3	11	19	35	15
Puducherry	0	0	0	0	0	0	0	0	0	0	0	0
Punjab	13	22	23	466	1600	10	2	5	123	4883	1015	30
Rajasthan	4	6	35	41	35	2	6	3	1	31	9	4
Sikkim	1	0	1	1	0	0	0	0	0	0	0	1
Tamil Nadu	24	94	138	22	17	12	15	14	16	9	4	9
Tripura	1	10	354	339	0	0	0	0	0	0	1	0
Uttar Pradesh	71	126	170	339	176	27	5	2	6	61	156	199
Uttarakhand	30	36	97	154	181	103	1	0	0	10	22	37
West Bengal	4	27	41	5	2	0	0	1	5	3	1	5

Source: NASA FIRMS data for India. Highlighted cells represent state-month values lying in the 10th decile of fire distribution.

Table A2
Height (in cm) by wealth class for women in India.

	Mean	Std. Dev.	Min	Max
Poorest	149.98	6.1	83.7	206.9
Poor	150.99	6.0	80.0	209.5
Middle	151.80	6.0	89.2	210.4
Rich	152.64	6.1	80.0	209.1
Richest	153.92	6.0	99.7	210.4

Source: Height for women from National Family Health Survey (IV) by wealth index.

Table A3
Biomass burning and height (full results).

	(1)	(2)
High Intensity Biomass Burning	−1.070*	
	(0.648)	
Prenatal – High Intensity Biomass Burning		−1.696**
		(0.708)
Postnatal – High Intensity Biomass Burning		−1.486**
		(0.598)

Table A3 (*Continued*)

	(1)	(2)
Age = 12 years	Base category	Base category
Age = 13 years	0.415	0.416
	(0.627)	(0.627)
Age = 14 years	0.537	0.534
	(0.792)	(0.792)
Age = 15 years	0.024	0.021
	(0.992)	(0.992)
Caste is SCST	−0.282	−0.288*
	(0.173)	(0.173)
Religion is Hindu	−0.479**	−0.479**
	(0.236)	(0.236)
HH Size	−0.015	−0.015
	(0.030)	(0.030)
Open defecation	−0.301	−0.301
	(0.199)	(0.199)
Poorest	Base category	Base category
Poor	0.591**	0.592**
	(0.257)	(0.257)
Middle	1.033***	1.033***
	(0.278)	(0.278)
Rich	1.548***	1.553***
	(0.307)	(0.307)
Richest	2.284***	2.287***
	(0.344)	(0.344)
Father's education level		
No Education	Base category	Base category
Class 1 to 5	−0.169	−0.166
	(0.235)	(0.235)
Class 6 to 11	0.084	0.085
	(0.242)	(0.242)
Class 12 or higher	0.790**	0.787**
	(0.342)	(0.342)
Mother's education level		
No Education	Base category	Base category
Class 1 to 5	0.381*	0.382*
	(0.213)	(0.213)
Class 6 to 11	0.764***	0.764***
	(0.227)	(0.227)
Class 12 or higher	2.133***	2.133***
	(0.405)	(0.405)
Mean rainfall in 75km radius	−0.068	−0.072
	(0.141)	(0.141)
Mean temperature in 75km radius	0.120*	0.129*
	(0.070)	(0.070)
Constant	145.314***	145.127***
	(1.979)	(1.968)
Observations	19,798	19,798
Fixed effects		
PSU	√	√
State*Year of Birth	√	√
State*Month of Birth	√	√
R^2	0.38	0.38

Note: Standard errors are clustered at PSU level. Observations are weighted using sample weights. Notation for *p*-values *** is $p < 0.01$, ** is $p < 0.05$ & * is $p < 0.1$.

Appendix B. Pollution and biomass burning

We also use data on PM2.5 to assess whether biomass burning is associated with changes in pollution levels. To address the paucity in ground-based pollution data in India, we estimate PM2.5 exposure using satellite data (Van Donkelaar et al., 2010). We use Aerosol Optical Data (AOD) retrieved at 0.5 × 0.5 degree resolution from Multiangle Imaging SpectroRadiometer (MISR). This data is converted to PM2.5 data (Liu et al., 2004; Kahn and Gaitley, 2015; Dey and Di Girolamo, 2010) using a spatially and temporally heterogeneous conversion factor (Dey et al., 2012). The PM2.5 data is further statistically downscaled to 0.1 × 0.1 degree resolution. The PM2.5 thus obtained is available at monthly frequency at 0.1 * 0.1 degree resolution (10 km*10 km grid). Using the grid points which fall within the 75 km radius, we calculate the mean PM2.5 in the 75 km radius around every PSU location for each month for time period 2001 to 2005. Similarly, we calculate: total count of biomass burning events occurring in the 75 km radius around the PSU location for each month, mean rainfall and temperature in the

Table B1
Pollution and fire activity.

Fire-events in 75 km radius (*z*-score)	2.806***
	(0.100)
Mean rainfall in 75 km radius	−0.908***
	(0.033)
Mean temperature in 75 km radius	−0.027
	(0.018)
Observations	172,610
Fixed effects	
PSU	√
Month*Year	√
R^2	0.57

Note: Standard errors are clustered at PSU level. Notation for *p*-values *** is $p < 0.01$, ** is $p < 0.05$ & * is $p < 0.1$. Analysis uses a PSU-Month-Year level dataset for time-period 2001–2005.

75 km radius around the PSU location for each month. This gives us a PSU level panel dataset which we use to explore the relationship between PM2.5 and occurrence of biomass burning events.

Literature supports the hypothesis that air quality deterioration has myriad negative effects on human health which can be the mechanism behind the negative results that we observe for adolescent height. We next provide suggestive evidence for this underlying mechanism. We explore the link between pollution and biomass burning by following empirical model outlined below:

$$PM2.5_{cmt} = \alpha_1 Fire_{cmt} + \alpha_2 Rainfall_{cmt} + \alpha_3 Temperature_{cmt} + \gamma_c + \rho_{mt} + \varepsilon_{cmt} \quad (3)$$

This model uses a PSU-year-month (cmt) panel to analyze whether change in pollution as measured by PM2.5 is affected by change in occurrence of fire-events ($Fire_{cmt}$) after controlling for weather conditions which play an important role in determining local pollution levels. The fire-events are normalized in this model, and changes are thus measured in terms of standard deviation units. This model includes PSU fixed effects to account for any place specific time-invariant characteristics and month-year specific fixed effects to account for seasonality present in the data. We find (Table B1) that a standard deviation increase in fire-events in the local area (75km radius circle with PSU location as the center) increases PM2.5 by 2.8 μg/m^3.

Appendix C. Difference-in-difference estimation description

Table C1
Number of periods of high biomass burning by conception month for states in 10th Decile of fire burning distribution (Table A2).

	Conception Month											
State	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Uttarakhand	2	3	4	4	3	2	2	2	2	2	2	2
Uttar Pradesh	6	7	8	7	6	5	5	5	6	7	7	6
Tripura	3	4	4	3	2	2	2	2	2	2	2	2
Punjab	4	5	6	6	5	4	4	5	6	6	5	4
Orissa	4	5	6	5	4	3	3	3	3	3	3	3
Nagaland	4	4	3	2	2	2	2	2	2	2	2	3
Mizoram	5	6	5	4	3	3	3	3	3	3	3	4
Meghalaya	2	2	2	1	1	1	1	1	1	1	1	1
Manipur	5	6	5	4	3	3	3	3	3	3	3	4
Maharashtra	5	6	5	4	3	3	3	3	3	3	3	4
Madhya Pradesh	3	4	3	3	2	2	2	2	2	2	2	2
Karnataka	4	4	3	2	2	2	2	2	2	2	2	3
Haryana	3	4	5	5	4	3	3	4	4	4	3	3
Chhatishgarh	3	4	4	3	2	2	2	2	2	2	2	2
Assam	3	4	4	3	2	2	2	2	2	2	2	2
Andhra Pradesh	4	4	3	2	2	2	2	2	2	2	2	3
Arunachal Pradesh	2	2	2	1	1	1	1	1	1	1	1	1

Notes: Highlighted cells represent conception months for which more than 4 periods (months) correspond to high burning period.

Table C2
Example: State of Assam – counting number of periods with high biomass burning by conception month.

Period		Conception Month Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Prenatal	1	1	2	3	4	5	6	7	8	9	10	11	12
Prenatal	2	2	3	4	5	6	7	8	9	10	11	12	1
Prenatal	3	3	4	5	6	7	8	9	10	11	12	1	2
Prenatal	4	4	5	6	7	8	9	10	11	12	1	2	3
Prenatal	5	5	6	7	8	9	10	11	12	1	2	3	4
Prenatal	6	6	7	8	9	10	11	12	1	2	3	4	5
Prenatal	7	7	8	9	10	11	12	1	2	3	4	5	6
Prenatal	8	8	9	10	11	12	1	2	3	4	5	6	7
Prenatal	9	9	10	11	12	1	2	3	4	5	6	7	8
Postnatal	10	10	11	12	1	2	3	4	5	6	7	8	9
Postnatal	11	11	12	1	2	3	4	5	6	7	8	9	10
Postnatal	12	12	1	2	3	4	5	6	7	8	9	10	11
Postnatal	13	1	2	3	4	5	6	7	8	9	10	11	12
Postnatal	14	2	3	4	5	6	7	8	9	10	11	12	1
Postnatal	15	3	4	5	6	7	8	9	10	11	12	1	2
Total		**3**	**4**	**4**	**3**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**

Notes: Highlighted cells represent months which experience high biomass burning.

Appendix D. Matching results

Table D1
Post-matching balancing of the variables in between two groups.

Variable	Mean		*t*-test	
	HIBB = 1	HIBB = 0	*t*-stat	*p* > *t*
Age = 12 or 13 years	0.65	0.66	−0.47	0.64
Age = 14 years	0.31	0.31	0.24	0.81
Age = 15 years	0.04	0.03	0.60	0.55
Caste is SCST	0.55	0.55	−0.13	0.89
Religion is Hindu	0.37	0.38	−0.65	0.52
Wealth category				
Poorest	0.03	0.03	0.27	0.79
Poor	0.10	0.11	−0.15	0.88
Middle	0.16	0.16	−0.30	0.76
Rich	0.30	0.31	−0.58	0.56
Richest	0.41	0.39	0.78	0.44
Father's education level				
No Education	0.10	0.09	0.86	0.39
Class 1 to 5	0.14	0.14	0.32	0.75
Class 6 to 11	0.65	0.66	−0.61	0.54
Class 12 or higher	0.12	0.12	−0.21	0.84
Mother's education level				
No Education	0.16	0.14	0.88	0.38
Class 1 to 5	0.21	0.19	0.73	0.47
Class 6 to 11	0.58	0.61	−1.46	0.15
Class 12 or higher	0.06	0.06	0.48	0.63
Housing Type = Pucca	0.33	0.34	−0.52	0.60
Housiehold has a toilet	0.92	0.93	−0.76	0.45
Rural Household	0.64	0.63	0.37	0.71
Household size >4	0.78	0.78	−0.22	0.83

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