# Fires, Wind, and Smoke: Air Pollution and Infant Mortality

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**ABSTRACT**

Globally, studies find an estimated 4 million people die prematurely because of air pollution every year. Much of this evidence relies on exposure-risk relations from studies focused on urban areas or uses extreme pollution events such as forest fires to identify the effect. Consequently, little is known about how air pollution impacts vulnerable subpopulations in the developing world where low incomes and limited access to health care in rural areas may heighten mortality risk. In this study, I exploit seasonal changes in air quality arising due to agricultural fires – a widespread practice used by farmers across the developing world to clear land for planting. Unlike large events like forest fires, agricultural fires are a marginal increase in pollution and thus reflect common levels of pollution exposure. I estimate the causal impact of air pollution on infant mortality at a countrywide scale by linking satellite imagery on the location and timing of more than 800,000 agricultural fires with air quality data from pollution monitoring stations and geocoded survey data on nearly half-a-million births across India over a ten-year period. To address the concern that fires may be more prevalent in wealthier agricultural regions, I use satellite data on wind direction to isolate the effect of upwind fires, controlling for other nearby fires. I find that a 10 $\mu g/m^3$ increase in PM10 results in more than 90,000 additional infant deaths per year, nearly twice the number found in previous studies. The mortality burden is much higher among rural households and the urban poor. These findings underscore the need to better understand the heterogeneity in pollution impacts and suggest that failure to do so results in underestimating these adverse effects.

***JEL:*** *Q56, Q53, O13, O15*
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# 1. Introduction

Air pollution is thought to be one of the leading contributors to premature mortality risk globally, but accurately quantifying the relationship between air quality and mortality in low- and middle- income countries remains a challenge. Estimating the causal effect of pollution on health requires overcoming various endogeneity concerns and is further complicated in the developing world due to a paucity of both pollution and health data. As a result, previous studies that have used plausibly exogenous sources of variation are limited in their spatial and temporal coverage. These are typically confined to urban areas and focus on vehicular or industrial sources of pollution. Other studies that have a wider geography usually examine the fallout from forest fires or other extreme events that lead to a short-term spike in ambient pollution. Both scenarios raise concerns of external validity. Additionally, they also typically lack the statistical power required to investigate the differential effects across subpopulations – for instance, rural and low-income urban households with limited options for avoidance behavior and low access to healthcare.

In this study, I overcome the empirical challenges outlined above by harnessing the marginal changes in air quality caused by seasonal agricultural fires used by farmers to clear land for agriculture and burn crop-residue after harvest. Using satellite data on agricultural fires and wind direction over India, I match the location and timing of each birth from a nationally representative household survey data to exposure from up-wind fires[1]. The identifying assumption is that after controlling for seasonal and other climatic variables, the variation in wind-direction and fire activity is unlikely to affect birth outcomes except through air pollution. I provide support for this assumption by using pollution monitoring station data to show that particulate levels increase due to up-wind fire activity but are not driven down-wind fires.

[1] Up-wind and down-wind throughout the text are used relative to a household's locations. Therefore up-wind fires refer to those fires that are in the direction that wind is blowing from at each household's location.

The approach used in this paper offers several improvements over previous studies investigating the link between air pollution and infant mortality. Agricultural fires occur across the country with a wide degree of seasonal and spatial variation (Figure 1). The household survey data used in this study records the complete birth histories for each woman interviewed which allows us to construct a dataset of nearly half-a-million births and their mortality outcomes from 2006 to 2016. In combination with changing wind direction, the data and the identification strategy allow me to measure the impact of variation in pollution exposure over a much larger area and time period than previous studies and investigate the heterogeneity in exposure-response relationships across subpopulations. A further advantage of this methodology is that it limits potential measurement error in exposure to pollution. Pollution monitoring stations are sparsely located in most developing countries and relying on monitoring data can lead to for measuring exposure can lead to attenuation towards zero, and result in underestimating the effect. Using satellite measures of agricultural fire activity along with geocoded household locations allows me to circumvent this measurement issue.

This study provides the first large-scale causal estimates of the infant mortality costs of air pollution in India. This developing country setting is of particular significance with 90 percent of the 4.2 million premature deaths attributed to ambient air pollution in 2015 occurring in low- and middle-income countries (WHO 2018). Along with India, the use of agricultural fires is growing across many developing countries. Crop-residue burning alone is estimated to contribute nearly 30,000 gigagrams of carbon dioxide equivalents (more than four times the total emissions from the transportation sector in the U.S) in 2016 (FAO 2018.; US EPA 2018). These emissions have grown by more than 1.2 percent per year on average within the 2006 – 2016 period (FAO 2018). Therefore, the results in this study have significant implications for other low-income countries that are seeing widespread use of agricultural fires.

Agricultural fires are used in India to clear land for crops as well as burn stubble left on fields after harvest. Both types of burning are estimated to contribute to the air pollution in India and surrounding regions (Venkataraman *et al*. 2006). Crop-residue burning is estimated to contribute as much as half of the particulate pollution in some cities in India during harvest seasons (Kaskaoutis *et al*. 2014; Cusworth *et al*. 2018). The location of these fires is driven by agricultural practices, including the expansion of mechanical harvesting (Gupta 2012). In central and north-eastern parts of India, farmers frequently burn forest growth to clear land for their one crop per year, where they practice rain-fed agriculture associated with low yields (Venkataraman *et al*. 2006). In contrast, crop-residue burning is also common in the agriculturally productive regions of the Indo-Gangetic plain where farmers have access to irrigation and plant two or more seasons of crops during a year. Given these underlying drivers of crop residue burning, the location of agricultural fires is likely to be correlated with other factors that influence child health outcomes, complicating the empirical estimation of the effects of such fires on infant mortality. I overcome this identification challenge by isolating the effect of exposure to agricultural fires that occur up-wind of a households' location and show that pollution levels increase only from up-wind fires.

I draw upon multiple satellite data sources to assemble a spatial panel dataset on agricultural fire activity, wind conditions and other climatic variables across India spanning a ten-year period. Using administrative data from the government of India's Central Pollution Control Board, I also construct a monthly panel of air pollution measures for over 250 cities for 2013-15. Finally, I combine the satellite measures of fire activity and wind direction with information on infant births and mortality outcomes from a geocoded national scale household survey – the National Family and Health Survey 4 (IIPS 2017). Using these data, I present two sets of empirical results. First, I document the impact of agricultural fires on pollution measures. Second, I present estimates of fires on the effect on neonatal and infant mortality and other birth outcomes. In both cases, the identification strategy is similar in spirit to a difference-in-differences approach. I compare the changes in the outcome (pollution or mortality rates) within the same season over different years, and across locations with high versus locations with a low number of up-wind fires. The main specification estimating the mortality effects controls for season time-trends flexibly for each sample cluster in the NFHS survey. Each sample cluster is approximately analogous to a village. This specification compares changes in mortality amongst children born within the same season in the same village, across different years. The results remain robust to the use of mother fixed effects which compares the birth outcomes for siblings born under different pollution exposure levels. Alternative fixed effects which control flexibly for season and location at slightly higher levels of aggregation such as district or state also show similar results. I also undertake sensitivity tests varying the catchment area (i.e. buffer) used to calculate the fire exposure around each household location and find that the estimates remain consistent. Finally, I also show that fire exposure during months 13-14 after birth and 1-2 months after birth do no predict mortality within the first year or the month of birth, respectively. These additional tests reduce the concern that these pollution impacts might be driven by other unobserved factors.

To first measure the effect of agricultural fires on pollution, I combine the air quality measures with the agricultural fires and wind data to calculate the incidence of up-wind fires at the city-month level. Consistent with previous work on the pollution impact of agricultural fires in India within the atmospheric sciences literature (T. Liu *et al*. 2018; Kaskaoutis *et al*. 2014), I find that up-wind agricultural fires have a robust and significant effect on particulate matter (as measured by PM10 levels). These results are also consistent with a growing set of studies within economics that utilize wind movements to construct a plausibly exogenous source of variation in pollution (Deryugina *et al*. 2018; Rangel and Vogl 2017; Anderson 2016). Additionally, I also show that down-wind fires do not affect the pollution level. Further, I find that the impact of up-wind fires on PM10 is non-linear. Low levels of fire activity (less than four fires in the month) do not affect PM10, whereas a higher intensity of fires (5 or more fires) increases PM10 levels by an average of more than 3 percent.

The main results in the paper focus on the impact of exposure to up-wind agricultural fires during *in-utero* months on infant birth outcomes. Previous studies within both economics and the medical literature find an increase in the mortality risk due to pollution exposure during pregnancy. While it is known that embryos and fetuses are susceptible to damage from air pollution, the biological mechanisms that link *in-utero* pollution exposure to adverse birth outcomes are still debated. Recent medical studies hypothesize that air pollution potentially leads to oxidative stress, inflammation, and hemodynamic changes that damage oxygen and nutrient transport to the fetus (La Marca and Gava 2018). The period of the pregnancy in which pollution exposure is most relevant for infant mortality is likely to vary by the type of pollutant (Lacasaña, Esplugues, and Ballester 2005). However, some recent systematic reviews of available data suggest that the effect is most pronounced during the third trimester of pregnancy when oxidative stress within the womb might be higher (Beate Ritz and Wilhelm 2008; Stieb *et al*. 2012). The data and the availability of pollution exposure measures over a long time period allows me to explore the effect across the *in-utero* months in this study.

I use data from birth histories of women aged 15-49 interviewed in the National Family and Health Survey (NFHS 4) limiting the sample to births recorded within the last ten years (from 2006 – 2016) to minimize recall errors. I include birth histories of only those women who have resided in the same location since the birth was recorded to avoid measurement error due to migration. The birth histories provide information on the month and year of their birth, whether the child survived and if died, the age at which they died. Using this information, I construct measures of *in utero* agricultural fire exposure, i.e., the number of fires that were within a certain radius up-wind of the household's location during each of the months that the mother was pregnant. I then estimate the impact on mortality using exposure for each of the *in-utero* months. For both neonatal and infant mortality, exposure during the late pregnancy months and the month of birth is found to have the most substantial effect. The significance of exposure during the final months of pregnancy is consistent with results from previous studies in the economic literature. For instance, Jayachandran (2009) finds that exposure to pollution from Indonesian forest fires in the three months before birth has a strong effect on reducing survival. Rangel and Vogl (2017) also find that exposure to pollution from sugarcane burning during the last 13 weeks of gestation has a strong negative effect on birthweight. Similar adverse effects of exposure to particulate matter and carbon monoxide during the late pregnancy periods have been documented in epidemiological studies in the US as well (Wilhelm and Ritz 2005; B Ritz and Yu 1999).

The results from the preferred specification that controls for season by sample cluster fixed effects show that exposure to pollution from up-wind agricultural fires increases neonatal mortality rate and infant mortality rate, while downwind fires have no effect. The increase in mortality ranges from by 2.7 additional deaths per 1000 births for neonatal mortality to 3.0 additional deaths for infant mortality - an increase of more than 8 percent and 6.7 percent relative to the sample mean of 33.3 neonatal and 45.4 infant deaths per 1000 births. These results also remain robust to varying the extent of the area around each household that is used to measure exposure to fires. I also examine the impact on mortality risk at age 5 and find similar, consistent results – *in-utero* exposure increases under-5 mortality rate by nearly six percent relative to the sample mean.

To compare these results with the existing literature on pollution exposure, I convert the effects of up-wind fires into mortality effects in terms of change in pollutant levels. Using the estimates from the effect of up-wind fires on PM10, I find that an increase in PM10 levels of 10 $\mu g\ per\ m^3$ results in an increase in infant mortality rate of 9.1 deaths per 1000 births, more than 20 percent of the sample infant mortality rate mean of 45.4 deaths per 1000 births. These effects are much higher than those found in Africa and Mexico City (Heft-Neal *et al*. 2018; Arceo, Hanna, and Oliva 2016) and similar to the 19 percent mortality effect found in China for the 0-4 age group (He, Fan, and Zhou 2016).

I then examine the differential effects across various subpopulations by interacting the up-wind fire exposure variable with sample characteristics. The adverse effects are driven entirely by the mortality impact of agricultural fires within rural areas. Neonatal mortality increases by 3.2 and infant mortality by 3.7 additional deaths per 1000 births. The results also show a similar pattern for under-5 mortality – it increases in rural areas by more than six percent, while there is no effect in urban regions. While the overall effect in urban regions is relatively muted, I find that poorer urban households fare worse. However, wealth level does not change the mortality risk for rural households. I also find that children born to mothers who work as agricultural or manual labor are likely to have higher neonatal and infant mortality risk in rural areas. I do not see significant differential effects across gender of the birth, while higher order births are likely to be more susceptible to mortality risk. Overall, the results indicate that wealthier urban households may be able to undertake avoidance behavior such as staying indoors during pregnancy. They may also have better access to health and maternal care services such as deliveries in hospitals that could mitigate the immediate consequences of air pollution on birth outcomes. These urban-rural disparities are consistent with the findings in the previous literature that document the existence of higher pollution burden on rural residents (Neidell 2004; MAPS Working Group 2018).

Further, I find some evidence that down-wind fire activity is associated with a decline in the infant (12-month) and under-5 years mortality rate. This finding goes to show that fire activity is likely to be associated with other economic and agricultural productivity factors that appear positively correlated with 12-month survivability. Using data for a sub-sample of births for whom additional health inputs information is recorded I find that agricultural fire activity is positively associated with an increased likelihood of having delivered the birth at a hospital, formal health records for the child and increased vaccination rates in the first year. These health investments are likely to offset some of the adverse effects of the pollution exposure which is captured by the negative sign on down-wind fire activity. Therefore, it is essential to differentiate between exposures to up-wind versus down-wind fires.

Finally, I also look at the impact of agricultural fire exposure on birth-weight and find no evidence for a reduction in birth-weight. These results suggest that there might be selectivity in neonatal mortality such that weaker infants (who are likely to weigh less) have lower survival rates when exposed to agricultural fire pollution. However, the sample used in this analysis only includes births that occurred within five years of the survey, and the accuracy of recalled weights may be suspect (Channon, Padmadas, and McDonald

2011). I also estimate results for a smaller sample of births for whom birth-weights are reported from health cards or other written records. The null result remains for this sample as well.

This paper contributes to the growing literature from the fields of economics, environment, and epidemiology that examines the health burden of air pollution. Within economics, the focus has often been on modern, industrial sources of pollution within developed countries owing to the relatively better data availability on air quality measures (Graff Zivin and Neidell 2013). Recent work has expanded to look at the consequences of air pollution on health, education and labor market outcomes in developing countries (Greenstone and Hanna 2014; Bharadwaj *et al*. 2017; Hanna and Oliva 2015). Overall, these studies indicate a significant adverse effect on human capital outcomes. However, these studies are mostly limited to specific cities and focus on pollution sources that are more common in urban settings. One might be concerned that rural households, particularly in countries like India with a large population of rural poor, might be particularly vulnerable given that they are primarily engaged in outdoor work. Other studies that look at the effect of pollution from large-scale fires such as forest wildfires (Sastry 2002; Jayachandran 2009; Kim *et al*. 2017). While these studies shed light on the potential effects of biomass burning, such events studied are usually rare, with extreme levels of pollution. These results may differ from the effects that one would find in response to cyclical exposure to moderate levels of pollution that result from smaller, agricultural fires.

The closest previous study is by Rangel and Vogl (2017) who examine the effect of sugarcane residue burning in the state of São Paulo, Brazil, also exploiting the direction of the wind. Their analysis uses birth registry data from hospital records in 13 sugar-growing municipalities within São Paulo from 2009-2014, and the outcomes that they focus on are those observed immediately after birth. They find that exposure to fires results in adverse birth outcomes such as low birth-weight but find no impact on risk of mortality within the first day of life. This study adds to their result in several different ways. First, while their analysis is limited to the outcomes at birth, the NFHS data used in this study allows for an examination of not only health outcomes at birth but also the mortality risk at different periods of early childhood. Previous studies have found that fetal exposure to adverse temperature, rainfall and pollution has a significant impact on health outcomes in later-infancy, childhood and adult life as well (Almond and Currie 2011; Currie *et al*. 2014). Second, the context for their study differs from this paper in many characteristics. With a mostly urban population, São Paulo has a much lower infant mortality rate of 11 deaths per 1000 births, higher income and much better health delivery systems than India where the mortality rate is nearly four times higher (44 deaths per 1000 births, average of 2006-2016) (The World Bank 2018). As a result, the degree of vulnerability to air pollution in India may be much higher. This heightened risk is evidenced by the fact that they find no effect on mortality risk at birth, while the results from this study show a significant neonatal mortality cost due to agricultural fires. The nature of pollution exposure from agricultural fires is also likely to differ – sugarcane burning in Brazil occurs once a year as opposed to the seasonal agricultural fires that peak more than once a year and covers a much larger territory across India. Consequently, births exposed to fire emissions in India are much higher. The results in this paper are likely to be generalizable to other developing country contexts where agriculture associated fires are frequent.

I also take advantage of the nationally representative nature of the data to present estimates of the total number of deaths attributable to pollution exposure within the population. Population estimates indicate that the average number of neonatal deaths per year in India from all causes to be 0.8 million during the sample period (UN IGME 2018). Given this, the average impact from the regression estimates of an eight percent increase in neonatal mortality due to pollution implies that nearly 62,000 deaths per year occur due to *in-utero* exposure to pollution. Similarly, the average number of under-5 deaths per year for the sample period is estimated to be 1.47 million per year (UN IGME 2018). Given these mortality estimates, the results in this study imply an additional mortality burden of more than 90,000 under-5 deaths per year due to exposure to agricultural fires. In terms of pollution levels, the results imply that an increase in PM10 of 10 $\mu g\ per\ m^3$ results in more than 96,000 additional under-5 deaths per year. These estimates are a much larger mortality cost than thought previously. For instance, most recent disease burden models estimate about 51,000 under-5 deaths in India attributable to ambient air-pollution risk during 2015 (Lee and Kim 2018; Lelieveld, Haines, and Pozzer 2018). These estimates apply exposure-response functions based on studies mostly focused on developed countries or urban areas and have been found to underestimate the mortality impact of pollution in Africa as well (Heft-Neal *et al*. 2018).

## 2. Background: Agricultural fires in India

Agricultural burning has been used to clear land for agriculture and get rid of crop waste since the early periods of human history (Brandt 1966). Limited use of fires, under controlled conditions, can help in land renewal, removal of invasive species and pests and can provide other ecosystem benefits. In India, farmers use open field burning for two main purposes. First, it is used to clear stubble left on the field after harvesting and second, it is also used to clear undergrowth on lands left fallow between cropping seasons (Venkataraman *et al*. 2006).

There is a wide spatial and temporal gap between these two types of burning practices associated with agriculture in India. Crop-residue burning is mainly associated with the stubble left over from rice and wheat crop. Farmers employing the rice-wheat system usually grow rice in the monsoon or the *kharif* season. The crop is sown following the onset of monsoon rains in June-July and harvested during the months of October-November. Wheat is then planted as soon as possible in the wheat (*rabi*) season and harvested starting in April. Crop-residue fires are seen in post-harvest months corresponding to these cropping seasons in areas where the rice-wheat system is dominant such as in the states of Punjab, Haryana, Uttar Pradesh, Bihar, and Himachal Pradesh. Under the rice-wheat system, farmers have a limited window within which they need to harvest and clear their field before planting next season's crop. A crucial input in this quick turnaround has been the use of combined harvesters. The harvester usually spreads the crop residue in the fields which can be time and labor intensive for farmers to collect. As a result, farmers tend to burn this residue to clear their fields quickly and at a low cost (Kumar, Kumar, and Joshi 2015). These fires are often observed within proximity to urban areas. Delhi, the capital city, is particularly prone to high levels of pollution from post-harvest fires (Cusworth *et al*. 2018; Chandra and Sinha 2016; Ghosal and Chatterjee 2015). Consequently, much of the focus on agricultural fires in India has been on such crop-residue burning practices.

In contrast to crop-residue burning, previous literature has mostly ignored the pollution and health implications of fires used for clearing agricultural land. These fires mostly occur close to forest lands in central and north-east India (Venkataraman *et al*. 2006). Farmers in these regions usually plant one season of rice and then leave the land empty after harvest. Many follow "shifting" agriculture where the land is left fallow for more than a year, and the farmers switch between alternate plots of land across years (Ramakrishnan 1992). These fallow lands may be overtaken by undergrowth and weeds which need to be removed before planting the next rice season. Farmers resort to the use of fire to clear these lands, and such fires peak during February to May (Venkataraman *et al*. 2006).

The effect of seasonal crop-residue burning on pollution levels in India has been a source of growing concern for policymakers and researchers. Several studies in the fields of atmospheric and environmental sciences have examined the emissions from these fires. These studies use a combination of atmospheric modeling methods and statistical analysis and mostly focus on a specific city or region, primarily in the vicinity of the rice-wheat system states. Across sites, these studies have documented a significant increase in particulate matter (PM10 and PM2.5), aerosol concentrations as well as sulfur and nitrous oxide levels associated with increased agricultural fire activity. For instance, Mittal *et al*. (2009) find an increase in PM 2.5 of more than 547 micrograms per cubic meter in the city of Patiala in Punjab. Cusworth *et al*. (2018) estimate that up to 78% of the PM2.5 increases in Delhi can be attributed to agricultural fires during peak harvest seasons in some years. Similar associations have been found over a larger region of analysis as well. Mishra and

Shibata (2012) find that aerosol optical depth increases by 0.1 – 0.3 over the Indo-Gangetic Plain during seasons with agricultural fires.  No studies have related this increase in pollution in India to health outcomes. The results that I present in this study on the impact of agricultural fires on pollution measures are consistent with those found in much of this literature.

## 3. Data

### 3.1 Agricultural fires

Administrative data on agricultural fire incidents are not available in much of the developing world, and India is no exception. However, it is possible to detect fires from space using satellite-derived thermal information. I use fire detection data accessed from the MODIS (Terra and Aqua datasets) Fire Mapper product (collection 5, spatial resolution 1 × 1 km) provided by the Fire Information for Resource Management System (FIRMS)[2]. The algorithm used to detect fire activity exploits the intense emission of mid-infrared radiation from fires (Giglio *et al*. 2003). The MODIS algorithm examines the radiation from each pixel of the MODIS swath and flags it as having a fire if at least one thermal anomaly is detected within that pixel (NASA 2018). The dataset consists of a daily record of these fire pixels along with geographic coordinates that correspond to the approximate center for each pixel. A pixel corresponds to an area of about one square kilometer on the ground.

The algorithm detects both actively burning fires and smoldering patches. The data are acquired by the satellites at least once daily over the whole Indian region. Giglio *et al*. (2003) note that fires under 1000 square-meters are detectable under average conditions, which corresponds to about one-tenth the size of an average agricultural field size in India

[2] Available online at: https://earthdata.nasa.gov/active-fire-data

of about 1.15 hectare (Bodh *et al*. 2016) and therefore provides a high degree of confidence that majority of the on-field agricultural fires are captured in the data.

There are a couple of caveats to be noted about the use of MODIS fire data product. First, the data corresponds to "fire pixels" having at least one fire, and there is no way of knowing how many fires are within each pixel. So, the fire counts may be an underestimate of the actual number of fires that are on the ground within each pixel. Second, while most of the fires recorded in the data are vegetation fires, it is possible that volcanic eruptions or flares from gas wells may also be detected as thermal anomalies and flagged as fire pixels. This is less of an issue in the context of this study since the Indian region has no active volcanoes on the mainland, and most natural gas wells are located offshore.

There are more than 800,000 pixels with fire activity during the study period from 2006-2016. For each such fire pixel, the data record the location and the detection date. Figure 1 shows the seasonal variation in the agricultural fire incidents recorded by the MODIS instrument over the sample period. Panel (a) of the figure portrays the fires recorded from February to June. These fires correspond to the land clearing fires used by farmers mostly in the north-eastern states of the country and some in the central regions as well. We also find some fire activity in the north and north-west regions which corresponds to the burning of crop-residue left on the field after the winter crop harvest. Panel (b) of Figure 1 shows the fires that occur from September to January. This period corresponds to the harvesting of the monsoon (*kharif*) crop, mostly rice. The fire activity is predominantly concentrated in the northern regions of the country, around the states of Punjab, Haryana, and parts of western Uttar Pradesh.

### 3.2 Pollution measures

I obtain daily pollution meter data from the Central Pollution Control Board (CPCB 2018). The CPCB operates under the aegis of the Ministry of Environment, Forest and

Climate Change of the Government of India and is the primary regulatory and monitoring agency for environmental pollution. Ground-based measurements of air pollution levels in India are limited to urban areas and not available for much of the rural hinterland. Given these limitations, I focus on examining the link between agricultural fires and air quality within nearby cities. The pollution meters record data on sulfur dioxide ($SO_2$), and particulate matter (PM10), and nitrogen dioxide ($NO_2$) for a sub-sample of cities.

Figure 2 shows the distribution of the cities for which the pollution meter data are available. The number of pollution monitoring stations per city varies from a single monitoring station for smaller cities to a maximum of 19 stations for larger cities such as Delhi or Mumbai, with a median of 3 stations. I limit the sample of observations to recent years (2013-15) in the dataset for which consistent coverage is available. I also aggregate the pollution measures to the monthly average level in each city. In total, the final dataset consists of more than 250 cities, spanning the period from January 2013 to December 2015. Table 1 in the appendix presents descriptive statistics on the number of fire counts with a 75 km radius around each city center.

### 3.3 Wind direction and other climate variables

The critical atmospheric information that I utilize in the identification strategy is the wind direction over the locations of interest. The data for constructing this variable comes from the Remote Sensing Systems Cross-Calibrated Multi-Platform (CCMP) vector wind analysis product (Version 2.0)[3]. The CCMP wind data product has near-global coverage with high-spatial and temporal resolution, starting in 1987 (Ricciardulli 2017). I obtain a 0.25 degree gridded wind vector data at the monthly level from 2006 – 2016 (Wentz *et al*., n.d.). The wind data are a combination of satellite, ground-based and wind model measurements; further details are documented in Atlas *et al*. (2011). The data are in the form of the monthly mean horizontal (U) and vertical (V) components of the wind

[3] CCMP Version-2.0 vector wind analyses are produced by Remote Sensing Systems. Data are available at www.remss.com.

vector for each grid cell. The U and V components are relative to true north, i.e., they have positive values if the wind is blowing towards the north-east direction. Using these two components, I calculate the wind direction using the standard trigonometric function

$$\theta = arctan2(V, U) \tag{1}$$

where $\theta \in (-\pi, \pi]$, is the angle (in radians) relative to the positive x-axis. I then use this direction to classify the wind direction to one of eight octants. Going clockwise from north, these octants range from north-to-north-east (NNE) when $\frac{\pi}{4} \leq \theta < \frac{\pi}{2}$ to north-west-to-north (NWN) when $\frac{\pi}{2} \leq \theta < \frac{3\pi}{4}$.

In addition to the wind data, I also use satellite and climatic model-based data on temperature and precipitation. Temperature and rainfall shocks have been found to affect mortality and human health in a variety of contexts, including India (Burgess *et al*. 2017; Maccini and Yang 2009), further, they might affect the dispersion of smoke from the fires. Therefore, I control for these factors in the estimates. The temperature data are retrieved from the Global Historical Climatology Network (version 2) and the Climate Anomaly Monitoring System (GHCN CAMS). GHCN CAMS is a high resolution (0.5x0.5 degree) analyzed global land surface temperatures from 1948 to near present[4]. GHCN CAMS uses data from station observations across the globe combined with interpolation techniques to construct the gridded data. Fan and van den Dool (2008) describe the process in detail. Rainfall data come from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS). CHIRPS uses satellite imagery along with in-situ station data to create a gridded rainfall product at a very high spatial resolution and available in near real-time (Funk *et al*. 2015). I use monthly average rainfall data from CHIRPS with 0.05 x 0.05-degree spatial resolution over the 2006-2016 period. I use a distance weighted interpolation method to estimate the wind,

[4] These data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their web site at https://www.esrl.noaa.gov/psd

temperature and precipitation data values at the point locations of the cities in case of the pollution results, or the sample clusters when examining the impact on infant mortality[5].

### 3.4 Infant mortality and birth outcomes data

The data for the outcome measures of infant mortality and health come from the National Family and Health Survey – IV (NFHS 4). The NFHS is the Demographic and Health Survey (DHS) equivalent in India. The NFHS 4 survey collected data from January 2015 – December 2016 from over 600,000 households covering all areas of the country (IIPS 2017). This sample size was much larger than previous rounds of the NFHS (nearly four times larger than in NFHS 3), and the sample was designed to be representative at the district level. For each sample household, the NFHS 4 survey canvassed four questionnaires: a household questionnaire, a woman's questionnaire, a man's questionnaire and a biomarker survey (IIPS 2017).

The main variables in this analysis come from the woman's questionnaire. The NFHS interviews all eligible women between the ages of 15-49 within each sample household on a variety of issues. Each woman is asked about her entire reproductive history thereby providing details on the birth histories of all children ever born to her. The birth histories include information on when a child was born (month and year), their gender, and birth order. The survey also records whether the child is currently alive, and if not, the the age at which the child died is collected. For births that occurred within five years of the survey, the woman is also asked about other birth outcomes including the child's weight at birth. The analysis of infant mortality that I carry out uses this recall data on child births

[5] The results are similar across a variety of interpolation methods including bilinear or cubic spline estimates.

and deaths. For the whole sample of women interviewed in the NFHS 4, a total of 1,315,617 births are recorded in the birth history data.

The use of recall birth history data may lead to potential measurement error. For instance, the selective omission of those births that did not survive from the birth histories would result in an underestimation of mortality (IIPS 2017). However, the infant mortality rates from the NFHS birth history data are very close to the mortality statistics that the Census Bureau of India provides based on its Sample Registration System (SRS) of births lending support to the accuracy of deaths reported in the recalled birth history in the NFHS. I provide further details later when discussing the descriptive statistics.

A second potential source of error could arise from measurement error in the recall of the timing of births and deaths. To minimize such bias, I limit the sample used in the main set of estimates to births recorded within the past ten years before the survey (about 472,000 births). The results are robust to varying this recall time horizon. Finally, exposure to pollution from agricultural fires could be mismeasured if the child was born in a different location than the location in which the household currently resides. The NFHS records information on how long the individual has resided in this location. I utilize these data to restrict my sample to only those births that have occurred since the interviewed woman has been residing in the current location. By doing so, I exclude about 12 percent of the births within the past ten years.

From an empirical standpoint, one of the main advantages of using the NFHS 4 data for this analysis is the availability of geo-referenced sample clusters. There are more than 28000 sample clusters in NFHS 4, with each cluster containing an average of 46 households. To ensure respondent confidentiality the cluster GPS latitude/longitude coordinates are randomly displaced in the public NFHS 4 data files. Urban clusters are displaced between 0 2 kilometers, and rural clusters are displaced between 0 and 5 kilometers. Further, about 1% of the rural clusters are displaced up to 10 kilometers. In all cases, the displacement is restricted so that the final coordinates lie within the boundaries of the original district from which the households were sampled. I minimize the spatial measurement error by using agricultural fire exposure over a much larger buffer of 75 kilometers around each cluster that accounts for any error due to the displacement in the clusters' coordinates. Also, the results remain robust to varying the buffer radius. Table 1 in the appendix presents descriptive statistics on the number of fire counts in the in-utero months within a buffer of 75 km radius.

## 4. Empirical methodology

The empirical methodology for measuring the impact of agricultural fires on pollution as well as infant outcomes is similar. The main estimation equation is of the following form:

$$y_{i,c,m,y} = \beta_0 + \sum_{k=1}^{n} \beta_k * F_{up,c,r}^{k} + \sum_{k=1}^{n} \delta_k * F_{down,c,r}^{k} + \gamma F_{other,c,r} + \alpha^t T_{c,m,y} + \alpha^r \mathrm{Precip}_{c,m,y} + \boldsymbol{X'}_{\boldsymbol{i}}\Gamma + \mu_{c,q} + \eta_{q,y} + \lambda_m + \varepsilon_{i,c,m,y} \qquad (2)$$

where $y_{i,c,m,y}$ is the outcome variable. In the pollution equation, the outcome variable is the PM10 levels measured in city $c$, in month $m$, for year $y$. In the case of infant birth outcomes, the outcome variable is the birth outcome for individual $i$, born in cluster $c$, during month $m$, and year $y$. When the outcome is mortality, I scale this variable so that it takes the value 0 when the individual survives and takes the value 1000 if the individual dies. This allows for the coefficients to be interpreted in terms of standard mortality rate measured as deaths per 1000 births. $F^k_{up,c,r}$, the main variable of interest is a measure of the exposure to up-wind fires (described below). I also control for measures of down-wind fire ($F^k_{down,c,r}$) as well as fires that are in other (neither up- or down- wind) directions $F_{other,c,r}$. Additional controls include month-year mean temperature and precipitation ($T_{c,m,y}$ and $\text{Precip}_{c,m,y}$). I control for the mean temperature and precipitation during *in*-utero months including the square of the mean temperature and rainfall as well as their interaction. I also control for individual, maternal and household characteristics such as the gender of the child, maternal age and education, religion, caste group, household asset index and other factors. The regression equation includes location specific seasonal fixed effects (city- or cluster-by-quarter of birth fixed effects) $\mu_{c,q}$, year specific seasonal fixed effects (quarter of birth-by-year of birth fixed effects) $\eta_{q,y}$ , and month of birth dummies $\lambda_m$. This specification flexibly accounts for city/cluster specific seasonal trends, and controls for time invariant spatial and seasonal (quarter) unobservable characteristics within each city/cluster. The identification is therefore based on comparing the change in outcomes within a city- or cluster-quarter over different years with respect to change in the intensity of up-wind agricultural fires.

For the heterogeneity analysis, I interact the up-wind fire exposure variable with key characteristics to examine differential effects across various dimensions. I also present results from using alternative fixed effects specifications. In particular, given that nearly 80 percent of the women in the sample have more than one child, I present results using mother fixed effects as well. This specification compares the change in mortality outcome within siblings exposed to varying levels of pollution *in-utero*.

I construct measures of exposure to agricultural fires around each city or cluster $c$ for month $m$ in year $y$ as follows. I first find the prevailing wind direction for each month-year for each city or cluster using the gridded wind product. Second, I calculate the number of fires around each $c$ within varying radii, as well as the bearing (angle) between each fire in the buffers and the location of $c$. I then create counts of the fires in each octant (45-degree sectors) of the circular buffer. Using the wind direction and location of these fires, I aggregate the fires that are up- and down-wind of each cluster or city. For instance, if the wind is blowing from the southwest-west (SWW) octant towards north-northeast octant (NNE), then the fires that are in the SWW direction are up-wind fires ($F_{up,c,r}$) and those in the NNE direction are down-wind ($F_{down,c,r}$). I first present results for the pollution impact using a flexible specification of the $F_{up}$ and $F_{down}$ and show evidence for the non-linear effect of the up-wind fires. Based on these initial results, the main specification that I use relies on splitting the fire counts into bins.

## 5. Impact of agricultural fires on pollution

### 5.1 Preliminary evidence

I use the daily air quality measures from the Central Pollution Control Board (CPCB) for 257 cities during 2013-2015 to estimate the effect of agricultural fires on pollution. While many cities have more than one pollution measuring station, data on the location of each measuring station is unavailable. Therefore, I aggregate air quality measures to the city level. I geocode the city locations at the approximate center of each city and use this as the reference to calculate the fire counts as well as to interpolate the wind and other climatic variables. The primary air quality measure that I focus on is the level of particulate matter measured by PM10 levels in micrograms per cubic meter ($\mu$g/$m^3$). I also have data on sulfur dioxide for this period, and measures of nitrogen dioxide for some cities (130 out of the 257 cities), and I present results of the impact of fires on these measures in the appendix.

I first present descriptive evidence showing the link between pollution and agricultural fires. Figure 3 shows the weekly variation in the average value of PM10 across all the sample cities for the year 2015. Also shown in the same plot is the average weekly number of fires in the up-wind direction within 100 km of each city. The PM10 levels and the number of fires track closely with each other. Two additional points stand out from this figure. First, we see two definite periods of high fire activity that correspond to the seasonal variation in fires described earlier and shown in Figure 1 for the whole sample period. Second, the PM10 levels, on average, are several magnitudes higher than safe air quality standards for this sample of India cities. The mean PM10 level is 93.3 which is more than four times the WHO prescribed safe level of 20 $\mu g/m^3$ annual mean (World Health Organization 2006, 9) and more than 1.5 times the CPCB prescribed standard of 60 $\mu g/m^3$ per year. The average PM10 levels remain much higher than these safe levels even during the weeks when fire activity is low.

A similar picture is presented by the descriptive statistics of the air pollution measures for the full sample period 2013 – 2015 in Table 1. Column (1) and (2) present the mean levels for city-months with above zero (the median) number of fires and with zero fires respectively, and column (3) presents the mean and standard deviation for the full sample. The difference in means in PM10 levels between (1) and (2) is nearly 15 units (Column (4)), more than 16% higher than the average PM10 value for the city-months with zero fires in Column (2). Similar higher average levels of $SO_2$ and $NO_2$ are also observed for the city-months with at least one up-wind fire. As with PM10 levels in 2015 seen in Figure 3, the overall PM10 average across the three-year period remains much higher than prescribed safe levels at more than 97 $\mu g/m^3$. Given these already high pollution levels, the marginal impact of a single fire within the vicinity of a city is likely to be small, but the effect is more likely to be detectable at higher levels of fire activity. This intuition is reflected in the regression results presented below.

5.2 Regression results

While the pollution data is at the daily level, analysis at this temporal scale is difficult due to missing data issues. Similar problems are documented previously in the economics and atmospheric science literature using these data in the Indian context (Burgess *et al*. 2017; T. Liu *et al*. 2018). Also, the infant birth outcome analysis can be performed only at the monthly level since only the month of birth is recorded. Therefore, to keep the analysis consistent between these two sets of results, I focus on estimating the pollution equation at the city-month level. I first estimate the regression equation (2) using a flexible functional form for the number of fires by using indicators for each fire from 1 to 9 and a separate category for a higher number of fires. I present these coefficients in Figure 4. The regression equations for both these figures control for fires in the other directions. Panel (a) presents the coefficients on the up-wind fire categories using a 75 km buffer around each city while panel (b) presents corresponding results for a 100 km buffer. In each case, we find graphical evidence suggesting a threshold effect wherein the marginal PM10 response is relatively flat for 1-4 fires but sees a definite increase when going beyond four fires.

Given this non-linearity that we observe in the effect of fires on PM10, I create three up-wind fire bins with ranges $\{0\}, [1,4], \geq 5$ corresponding to the overall pattern that we observe in Figure 4. Table 2 presents the results using these categories for up-wind fires and down-wind fires. Also, I control for the number of fires that are in the other directions (non-up/down fires). Consistent with Figure 4 we find that 1-4 up-wind fires do not increase PM10 levels, but we see a significant increase when there are five fires or more in a month. Down-wind fires show no impact. The results remain consistent when I increase the buffer radius from 75 km to 100 km. On average, the higher fire intensity categories increase PM10 by about 3.5% over the sample mean of 98.4 $\mu g/m^3$.

I present similar sets of results for the impact of up-wind fires on $SO_2$ and $NO_2$ in the appendix (Appendix Figures A1 and A2, Table A2). I find no evidence for the impact of the fires on $SO_2$ levels and limited evidence for an increase in $NO_2$ levels in the cities. These results for $SO_2$ and $NO_2$ are in contrast to the results reported by Mittal *et al*. (2009) who find an increase in the levels of both gases associated with postharvest months when crop-residue burning occurs. However, their study focused on data from five monitoring stations around a single city close to crop-residue burning locations in Punjab. The PM10 and $NO_2$ results here are consistent with those reported by Rangel and Vogel (2017) who also find that up-wind fires from sugarcane burning in Brazil increase PM10 but appear to have no effect on $NO_2$. Overall, the results of the pollution analysis indicate a robust relation between agricultural fires and PM10 levels measured by the air quality meters across a large sample of cities across India.

## 6. Impact on infant outcomes

### 6.1 Descriptive evidence

Table 3 provides descriptive statistics of the outcome variables as well as some of the key individual and household covariates. Column (1) and (2) provide the mean and standard deviation for births that are above and below the median number of up-wind fire exposure during the prenatal months. The median is equivalent to splitting the sample into births with at least one up-wind fire during the 0 – 9 months period before birth (about 45% of the sample) and those with zero (55% of the sample) fires since the median number of fires is zero. Column (3) presents the summary statistics for the whole sample while Column (4) presents the differences in means and results of the corresponding t-tests. Column (5) presents t-tests for the differences when we stratify by district-quarter dummies. For the overall sample, the average mortality rate measured at one month after birth is 33.4 deaths per 1000 births, and this increases to 45.25 deaths per 1000 births when mortality is measured at 12 months after birth. These mortality rates are very similar to the statistics from the Sample Registration System (SRS) which tracks births and death and is the primary source of vital demographic statistics in India (Bhat 2002)[6]. The average infant mortality rate (under 12 months) from the SRS for the years' corresponding to the sample period (2006-2016) is 45.27, almost precisely the sample mean in the NFHS data (NITI Aayog 2018).

The difference in means is indicative of higher mortality rates amongst births exposed to agricultural fires. The average neonatal and infant mortality rates are both significantly higher for births exposed to at least one up-wind fires, with 1.97 more neonatal deaths and 2.86 more deaths within 12 months after birth. Both these differences are more than 6% of their respective mean for the total sample. The differences in means remain significant in Column (5) which presents the results of the t-test after including district-by-quarter fixed effects[7].

The NFHS 4 also records birth-weights for the individuals born in the past five years before the survey. This sample numbers nearly 163,000, about 40% of the sample used in the mortality analysis. The birth-weight is reported from a health card or other written record if available. If no record is available, it is based on the mother's recall of the birth-weight. Previous analysis of NFHS birth-weights has found that accuracy of recalled weights may be suspect, with evidence of heaping around multiples of 500 grams (Channon, Padmadas, and McDonald 2011). Given these issues, I look at birth-weights for the whole sample, as well as for those for whom birth-weight data is based on written records (about 53% of the sample). When differences between birth-weight are examined for the whole sample, we find that infants exposed to at least one up-wind fire have a slightly higher birth-weight on average (about a 0.4% increase over the total sample mean).

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[6] The SRS undertakes continuous registration of births and deaths for a nationally representative sample of villages and urban blocks and is updated at a half-yearly period using surveys for updating and verification of deaths and births.

[7] The p-values in Column (5) correspond to those obtained by regressing the row variable on the group dummy (0 for below and 1 for above median) and district-by-quarter dummies. The p-values correspond to the coefficient on the group dummy.

The difference in means is not significant when comparing with district-quarter in Column (5). The difference in means of the birth-weight is also significantly reduced when I limit the birth-weight sample to observations with written records. I also use the birth-weights with written records to classify births that fall into low birth-weight (LBW) category. LBW individuals are those who weighed less than 2500 grams at birth (WHO 2014). The overall LBW share of births is about 17%, and there do not appear to be significant differences in the mean levels between the two groups.

In addition to the outcome variables, Table 3 also shows that significant differences exist between the two groups in terms of individual and maternal characteristics. Mothers are slightly older and have about half-a-year of education more amongst those exposed to agricultural fires. The households are also wealthier, based on the asset-based wealth index that the NFHS constructs. The asset wealth index is a principal component-based index of the household's ownership of assets such as television, bicycles, the material used for house construction, the source of drinking water and other factors. I control for all these covariates in the regression models that I estimate. These differences in covariates seen in Table 3 imply that the location of agricultural fire activity may not be exogenous and motivates the empirical methodology that I use in the regression estimates below.

## 6.2 Regression estimates

The main effects that I focus on are the impacts of pollution exposure on neonatal and infant mortality, although I also test for mortality under five years of age as well. The first month is believed to be the most vulnerable period of life, and globally neonatal mortality accounts for more than half of the total infant deaths (Do, Joshi, and Stolper 2018). Within the study sample, neonatal and infant mortality contribute 66.4 and 90.1 percent of the total under-5 mortality respectively. While neonatal and infant mortality do not account for all potential health costs, their high incidence makes them a substantial factor in the overall health burden of pollution. I also examine the effect on birthweight using the sub-sample of births for whom this data is recorded but find no evidence of any impact on either weight at birth in grams or on the incidence of low-birthweight (birthweight less than 2500 grams). These estimates are presented in the Appendix (Tables A4 and A5). I discuss the mortality effects below.

The first set of results I present consider the impact due to up-wind fire exposure during each month of the *in-utero* period, i.e., 0 to 9 months before birth. The estimation equation is identical to that shown in Equation (2) except for the addition of month-wise fire count categories for both up- and down-wind fires. For each month, I categorize the confidence-weighted count of fires in the up-wind octant into three bins - $\{0\}, [1,4], \geq 5$. These categories are consistent with the monthly fire count bins used in the regressions for measuring PM10 impact. Figure 5 presents these results for neonatal and infant mortality. The regressions include month-of-birth dummies, quarter-by-year fixed effects, and cluster-by-quarter fixed effects. Other control variables included are temperature, precipitation, and individual and household covariates.

The effect on both neonatal and infant mortality is most pronounced during the later stage of pregnancy from 0 to 2-months before birth. The higher vulnerability of infants to pollution exposure during the third trimester of pregnancy and just after birth is consistent with some of the earlier studies on air pollution and infant mortality. Biological literature suggests that maternal exposure to particulate matter and other air pollutants could lead to a decrease oxygen and nutrient supply to the fetus, and also result in adverse placental inflammation particularly during the final trimester (Beate Ritz and Wilhelm 2008; Stieb *et al*. 2012). Recent medical literature also hypothesizes that infants in the months before birth and neonatal stages may be more susceptible to pollution effects due to alveoli in the lungs being less developed (Hajat *et al*. 2007). Previous studies of exposure to biomass fires also find that the late pregnancy months have a strong effect on birth outcomes and mortality (Rangel and Vogl 2017; Jayachandran 2009). Chay and Greenstone (2003), find that particulate matter exposure increases mortality the most during one month period after birth, and much less in the following one year period during the early 1980s in the US. They note that evidence for the underlying biological pathways is unclear. Given these results, I focus on examining the impact of fire exposure in the late pregnancy months on birth outcomes in further detail below.

Table 4 presents regression results for the impact on neonatal mortality. Column (1) presents the results of the full sample using a 75 km radius around each NFHS cluster for measuring fire exposure. Consistent with the threshold effects seen in the PM10 results, we see no impact when exposed to four or fewer up-wind fires. Exposure to five or more up-wind fires increases mortality by more than 2.7 deaths per 1000 births relative to those exposed to no fires. Down-wind fires have no significant effect on mortality rate indicating that the channel through which agricultural fires impact birth outcomes is most likely through changes in air quality. This increase in neonatal mortality rate is about 8.2 percent relative to the average sample neonatal mortality rate of 33.3 deaths per 1000 births. The estimates remain very similar when I vary the exposure radius from 75 km to a 100 km buffer in Column (2). The magnitude of the coefficient on exposure to five or more fires remains very stable, and the remaining coefficients remain qualitatively the same as well.

Table 5 presents similar results for the impact on infant mortality. These results are also consistent with the finding that pollution from agricultural fires increases mortality risk. For the full sample (Columns (1) and (2)), the magnitude of the coefficient on five or more up-wind fires increases slightly to 2.8 – 3.0 additional deaths compared to the estimates for neonatal mortality. However, the effect size relative to the mean mortality rate in the sample of 45.4 deaths per 1000 births is smaller at about 6.7 percent. This pattern of results repeats in Table 6 which shows the effects on under-5 mortality. Here again, the negative effects of up-wind fire exposure are large and significant with around 3 additional deaths. Relative to the mean under-5 mortality rate of 50.1 deaths per 1000 within the sample, the share of pollution-related deaths linked to agricultural fires remains around six percent.

To compare these results with the existing literature on pollution exposure, I convert the effects of up-wind fires into mortality effects in terms of change in pollutant levels. To do so, I divide the coefficient on exposure to five fires or more in the mortality regressions by the coefficient on the effect of a similar number of up-wind fires on PM10. The resulting estimate is analogous to a Wald estimator. I assume that the marginal impact on PM10 levels estimated using the data from pollution meters from the 250 cities is extensible to the broader geographic region covered by the NFHS sample of births. For purposes of this discussion, I focus on the estimates from the regressions using the 75 km buffer. Appendix Table A3 provides details of these calculations.

The estimates in Table 2 show that up-wind fire activity of five or more fires increase PM10 levels by 3.3 $\mu g\ per\ m^3$ on average. Using a conversion factor of PM2.5 = 0.7∗PM10 similar to Heft-Neal *et al.* (2018) results in an equivalent increase of 2.3 $\mu g\ per\ m^3$ in terms of PM2.5. The effect of a similar level of up-wind fire activity on infant mortality rate is 3.03 additional deaths per 1000 births. This implies that an increase in PM10 levels of 10 $\mu g\ per\ m^3$ would result in an increase in infant mortality rate of 9.1 deaths per 1000 births, more than 20 percent of the mean infant mortality rate of 45.4 deaths per 1000 births in the sample. A similar increase in PM2.5 levels would imply an increase of nearly 13 deaths per 1000 births, about 28.6 percent of the sample mean. These effects are much higher than the infant mortality effect of 9.2 percent estimated by Heft-Neal *et al.* (2018) for a selection of African countries for an increase of 10 $\mu g\ per\ m^3$ in PM2.5. They are also larger than the 8.8 percent infant mortality estimated in Mexico City (Arceo, Hanna, and Oliva 2016) for an increase of 10 $\mu g\ per\ m^3$ in PM10. The impact I find is very similar to the 19 percent mortality effect for an increase of 10 $\mu g\ per\ m^3$ in PM10 levels found in China for the 0-4 age group (He, Fan, and Zhou 2016).

I also take advantage of the nationally representative nature of the data to present estimates of the total number of deaths attributable to pollution exposure within the population. I use the mortality numbers for India estimated by the UN Inter-agency Group for Child Mortality Estimation (UN IGME 2018). During the sample period 2006-2016, nearly 1.1 million infant mortality deaths occur per year on average, and the mean mortality rate is estimated to 43.4 per 1000 births. I apply the estimated pollution-induced mortality rate for a 10 unit increase in PM10 or PM2.5 to the population number of deaths, accounting for the population mortality rate and the fraction of the sample that is exposed to five or more fires (see Appendix Table A3 for details). This calculation results in an estimate of nearly 94,000 (135,000) additional infant deaths per year attributable to a 10 unit increase in PM10 (PM2.5).

These population mortality estimates can be compared to disease burden model-based estimates that are derived by applying exposure-response functions to spatial population data. The underlying integrated exposure-response functions measure the relative risk from ambient PM2.5 exposure using a theoretical minimum risk exposure level between 2.4 – 5.9 $\mu g\ per\ m^3$ compared to the ambient PM2.5 exposure levels derived from annual averages based on satellite data and chemical transport models (Cohen *et al*. 2017). These average ambient exposure levels used for India are in general much greater than the 10 $\mu g\ per\ m^3$ increase in particulate pollution that I use in calculating the mortality numbers above. For instance, in 2015 the annual average PM2.5 value for India was 74.3 $\mu g\ per\ m^3$ and the corresponding number of under-5 deaths were estimated to be around 51,000 (Lelieveld, Haines, and Pozzer 2018) – less than 40 percent of the number of under-5 deaths that I find using the pollution exposure results in this study. I also calculate average infant and under-5 deaths per annum for the 2006-2016 period using the Global Burden of Disease tool (GBD 2017) which also result in much lower estimates compared to the results that I find. For instance, the GBD estimate of about 70,000 infant deaths per annum is 52 percent of the estimated mortality burden that I find for a 10 $\mu g\ per\ m^3$ increase in PM2.5 and is closer to the number of deaths that my results imply for an increase of 5 $\mu g\ per\ m^3$ in PM2.5 (67,000 deaths per annum).

The GBD estimates apply exposure-response functions derived mostly from urban settings in developed countries and have been found to underestimate the mortality impact of pollution in Africa as well (Heft-Neal *et al*. 2018). This could be driven by the fact that households in developing countries are poor and are less likely to adopt avoidance behaviors. Consequently, the effect of air pollution is expected to be much higher (He, Fan, and Zhou 2016; Arceo, Hanna, and Oliva 2016). While I cannot directly test to see whether households engage in avoidance behavior, I present suggestive evidence in the results below by exploring the heterogeneity in pollution impacts across key population dimensions.

### 6.3 Heterogeneity in pollution effects on mortality

I first explore the difference in the mortality effects of pollution exposure between urban and rural populations. The urban and rural regions comprise 22 percent and 78 percent of the births respectively in the sample used for analysis. Columns (3) and (4) in Tables 4 – 6 present the regression estimates for the rural sample using 75 and 100 km buffers, while Column (5) to (6) present the same for the urban sample. The adverse mortality impact of pollution exposure is evident across all stages of early childhood in the rural sample, and the magnitude is larger than the corresponding coefficient on exposure to five or more up-wind fires seen within the full sample in Columns (1) and (2). Neonatal mortality increases by more than 3.1 deaths per 1000 births, infant mortality by 3.7 and under-5 mortality by a similar amount. These mortality impacts translate to about 9.2, 7.7 and 6.6 percent of the sample neonatal, infant and under-5 mortality, respectively. The magnitudes as a share of the sample mean are higher than in the overall sample even though the sample average mortality rates are higher in the rural areas.

While *down-wind* fires are not associated with changes in neonatal mortality rates, the infant and under-5 mortality results in the rural sample suggest that down-wind fires are potentially associated with a *reduction* in mortality rates. A plausible explanation for this finding is that overall agricultural fire activity is likely to be correlated with higher agricultural productivity, and consequently, households in such areas may have more resources to invest in early childhood health. I provide evidence to support this in Table 7 which looks at the association between total agricultural fire-activity (in the same 0-2 month before birth period) and indicators of health inputs. I use the data from a sub-sample of births within five years of the survey date for which the NFHS records several health input indicators. I find that fire activity is positively correlated with increased likelihood of institutional births and the mother having a card provided by a healthcare facility to keep track of the child's vaccination schedule and growth (Columns (1) and (2) of Table 7). The children in areas with higher agricultural fires are also more likely to receive critical vaccinations in their first year of life (Columns 3 – 5). These improved health inputs correlated with fire activity may offset some of the mortality effects later in childhood (under-12 months and under-5 mortality), but do not mitigate the adverse effects at early life (neonatal mortality within one month of birth). The sample for which the information is available for these variables is limited to the most recent birth recorded with the past five years, and the limited variation across these observations make it difficult to investigate the potential heterogeneity in mortality effects along these dimensions in greater detail.

In contrast to the heightened adverse effects on mortality in the rural areas, we do not see any effect on the mortality rates in urban areas due to up-wind fire exposure (Columns 5 and 6 in Tables 4-6). Part of the reason is potentially due to better antenatal and postnatal health care. The NFHS records several of these indicators for births that occurred within five years prior to the survey dates, and significant urban-rural differences are visible in these factors. 76 percent of the women in urban areas report receiving any antenatal care from a doctor for their most recent birth, while the corresponding number amongst rural women is just over 50 percent. The number of antenatal care visits are also lower amongst rural women.

Similarly, while more than 25 percent of rural births were delivered outside of a hospital (mostly at home), the share of such births among urban women is less than 12 percent. Delivery at a hospital is more likely to result in a postnatal check of the health of the infant in the first two days. These checks are likely to be critical in improving survival rates amongst those born with poor health conditions (International Institute for Population Sciences (IIPS) and ICF 2017).

In addition to healthcare availability and access, household wealth level is an important determinant of infant health outcomes. Panel A of Table 8 presents results examining the heterogeneity in mortality effects across household wealth. The regression specification used here adds interactions between up-wind fire exposure indicators and wealth level measured by the NFHS asset wealth index to the specification used earlier. The estimates are based on the 75 km buffer. Mortality risk due to pollution from up-wind fires does not vary with wealth level in the rural sample either in the neonatal stage or the first one year of life (Columns 1 and 3). However, wealth makes a difference to neonatal mortality in the urban sample. An increase in household wealth as measured by asset ownership reduces the neonatal mortality risk amongst urban births. This suggests that the urban poor may be more susceptible to adverse birth outcomes due to pollution exposure.

The remaining results in Table 8 examine the heterogeneity along other important dimensions. Panel B looks at differences across gender and Panel C across birth order. The mortality risk does not appear to vary across either of these factors. Panel D examines if mortality risk increases for those births whose mothers are engaged in agricultural or manual labor. Women who are work as labor may be more likely to work outdoors and later into their pregnancy term. As a result, they may face the risk of higher pollution exposure. The results in Panel D provide suggestive evidence for this mechanism, particularly in the rural sample. The coefficients on the interaction with exposure to five or more up-wind fires for the rural sample are much higher than the average mortality estimates seen earlier. Neonatal mortality is higher by more than 6 additional deaths per 1000 births and infant mortality by more than 10. However, the standard errors are generally less precise for these heterogeneity estimates.

### 6.4 Robustness tests

The first set of robustness tests take the form of a placebo regression in which I test that fires in the months after which mortality is measured do not predict mortality. For instance, up-wind fires during the second and third month should not explain mortality in the first month after birth. Similarly, fires in the 13$^{th}$ and 14$^{th}$ months should not effect infant mortality within the first 12 months after birth. Table 9 presents the results of these tests for neonatal and infant mortality in the rural sample using both 75 and 100 km radii for the buffer. The regressions include controls for down-wind and fires in other directions for the lead months as well. The coefficients on up-wind fires for the lead months are not statistically significant across the outcomes, irrespective of the radius used for measuring fire exposure. The *in-utero* up-wind fire coefficients remain consistent with those estimated earlier. These findings reduce the potential concern that there might be some other unobserved factors correlated with wind direction and agricultural fire activity that also drive mortality.

I also test the sensitivity of the results to other specifications. Columns (1) and (4) presents results from using an alternative set of fixed effects which flexibly control for state-specific seasonal effects and district-specific time trends along with month and birth-year effects. The coefficients show that neonatal and infant mortality effects remain consistent with the results from the preferred specification presented in earlier tables. Columns (2) and (4) show estimates from using mother fixed effects. This specification compares outcomes for siblings born to the same mother but having different levels of up-wind fire exposure. The results remain very similar to the results using cluster-by-quarter fixed effects. In columns (3) and (6), I show that the estimates in the main specification are robust to clustering by district rather than at the cluster level. The standard errors remain very similar to those obtained earlier. Overall, these additional tests provide added validity to the pollution impacts found in the study.

## 7. Conclusions

This study examines the adverse health consequences of *in-utero* pollution exposure on early childhood outcomes. The identification strategy uses seasonal variation in agricultural fires, a widespread practice among farmers in India as well as other parts of the developing world. To overcome the lack of ground-based measures of agricultural fires, I utilize satellite-derived data on the location and timing of agricultural fires at a high degree of spatial and temporal resolution. I combine the fire activity data with georeferenced daily pollution meter measurements from more than 250 Indian cities to first establish the impact of agricultural fires on levels of airborne particulates. I then leverage the birth history data of all women interviewed in the National Family and Health Survey (NFHS 4) to construct a panel of births and deaths at the month-by-year level for each NFHS sample cluster. Using these data, I then estimate the effect of exposure to agricultural fires on mortality and health outcomes at infancy. In both analyses, I exploit the variation in wind direction and isolate exposure to fires that are up-wind of the pollution meter or the household. This allows me to disentangle the potential income effect on infant health due to higher agricultural productivity or economic activity that be correlated with higher fire incidence. I show that both pollution and infant health are affected by fires that are up-wind, while down-wind fires have no effect.

The results show that up-wind fire activity has a significant effect on PM10 levels in the sample of Indian cities used in the analysis. Months that have 5 or more fires result in an average increase in PM10 levels of close to 4 $\mu g/m^3$ – 20 percent of the safe limit of 20 $\mu g/m^3$ prescribed by the World Health Organization (WHO). Rather surprisingly, this large impact of fires on PM10 levels is seen even though the average PM10 levels are already very high (mean of 98.4 $\mu g/m^3$) in the sample. These results are consistent with those seen in previous studies, largely in the environmental and atmospheric science literature, in India and those examining sugarcane burning in Brazil (Venkataraman *et al*. 2006; Mittal *et al*. 2009; Rangel and Vogl 2017).

The most potent effects of agricultural fire exposure on infant outcomes are seen in the higher likelihood of mortality across early childhood. Mortality rates within one month after birth (neonatal mortality) and during the first 12 months (infant mortality) show a significant increase with exposure to agricultural fires. I also find that the *in*-utero pollution exposure has lasting effects even up to five years of age leading to an increase in under-5 mortality rate of around 3 deaths per 1000 births. The increase in neonatal mortality is about 2.7 and infant mortality is nearly 3 deaths per 1000 births. These mortality costs are substantial even when India's high infant and child mortality levels are taken into account. The mortality effects of agricultural fire exposure amount to between 6 to 9 percent relative to the sample average of the mortality rates. These effects are concentrated in the sample of rural households, while urban areas show no evidence for an impact due to agricultural fire exposure. Differences is health care access as well household wealth may be potential factors underlying these differential effects.

At the aggregate, nationwide level, the results of this study imply nearly 94,000 (135,000) additional infant deaths per year attributable to a 10 unit increase in PM10 (PM2.5). These estimates signify a much larger mortality cost of pollution exposure than previously thought. For instance, recent studies estimate about 51,000 under-5 deaths in India attributable to ambient air-pollution risk during 2015 (Lee and Kim 2018) – less than 40 percent of the number of under-5 deaths that I find using the pollution exposure results in this study.

The results of this study add to the growing literature on air pollution and health. Unlike most previous studies in this area, this paper focuses on pollution from non-industrial, non-urban sources of pollution. I build upon previous research by improving measurement of exposure to the fires combining detailed georeferenced survey and satellite datasets. The large sample of births in the data also makes it possible to provide analysis at a much greater geographic scale, encompassing both urban and rural areas in the country. These results also highlight the public health implications of agricultural fires and the need for feasible policies to reduce such practices among farmers. Addressing the issue of crop-residue burning is going to be challenging since the expansion of mechanized harvesting through use of combined harvesters appears to be one of the drivers (Gupta 2012; Kumar, Kumar, and Joshi 2015). In recent years, there has been an increased focus on finding solutions for reducing crop-residue burning. Initial attempts, starting in 2015, to place a ban on any residue burning failed (Down to Earth 2017). Later, starting in 2018, the government in the state of Punjab has initiated policies to promote direct seeding machinery that can circumvent the need for clearing the residue from the field before planting, as well as subsidies for other residue management technologies (ET Bureau 2018). The potential for policies such as these to reduce the practice of crop-residue burning among farmers remains and subsequent effect on infant health remains to be seen.

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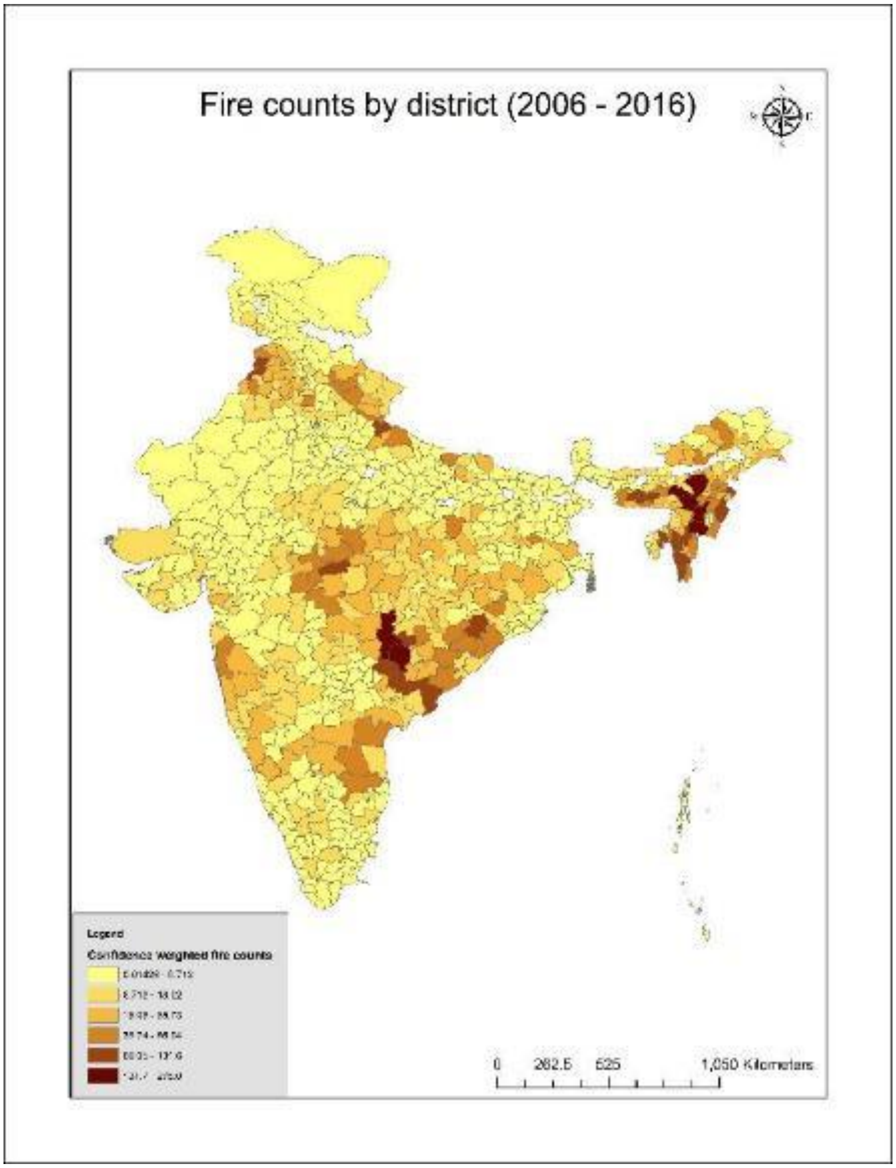
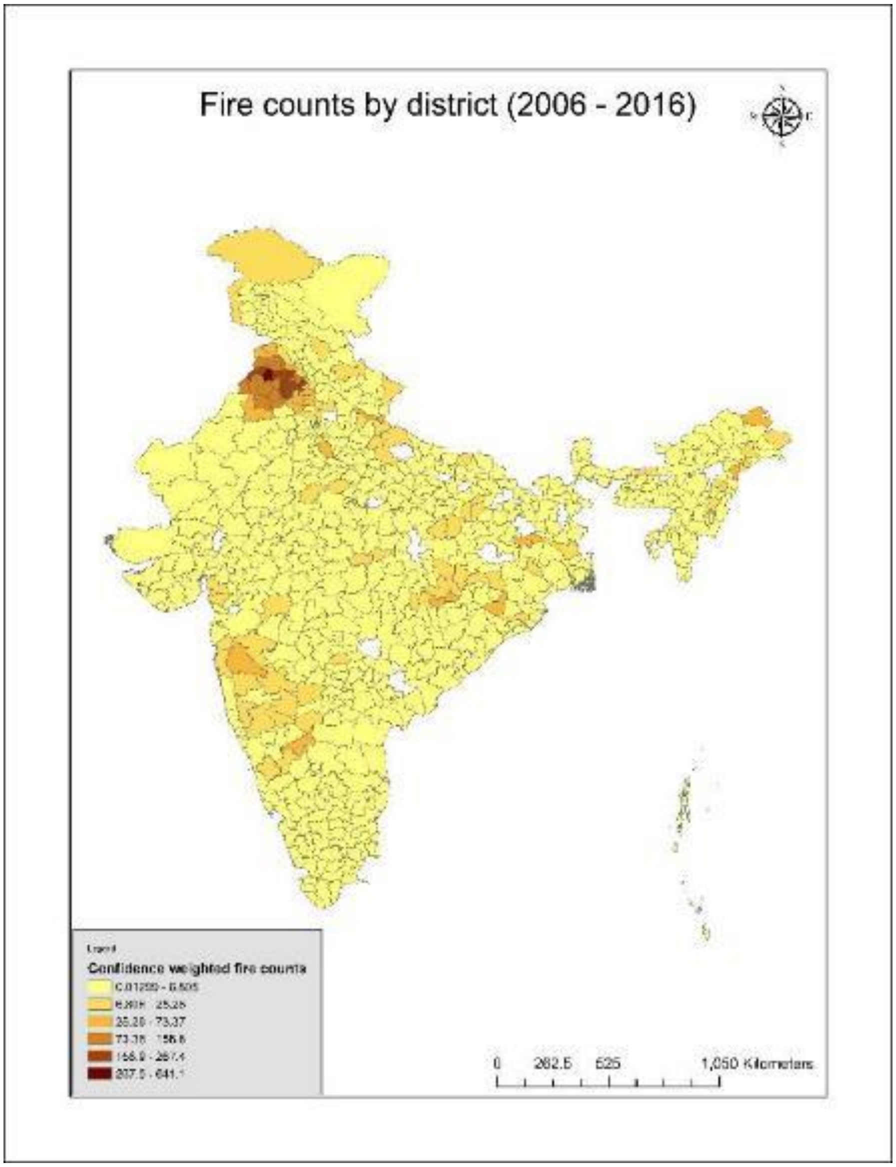
# Figures and Tables

**Figure 1: Seasonal and spatial distribution in agricultural fire activity**
**(a) February to June**




Note: Data based on MODIS instrument detected fire activity at the pixel level. The data covers the period from January 1, 2006, to December 31, 2016. The map shows the confidence-weighted number of fires in each district.

**Figure 1:** ***(cont.)*** **Seasonal and spatial distribution in agricultural fire activity**
**(b) September to January**




Note: Data based on MODIS instrument detected fire activity at the pixel level. The data covers the period from January 1, 2006, to December 31, 2016. The map shows the confidence-weighted number of fires in each district.

**Figure 2: Location of air quality meters**

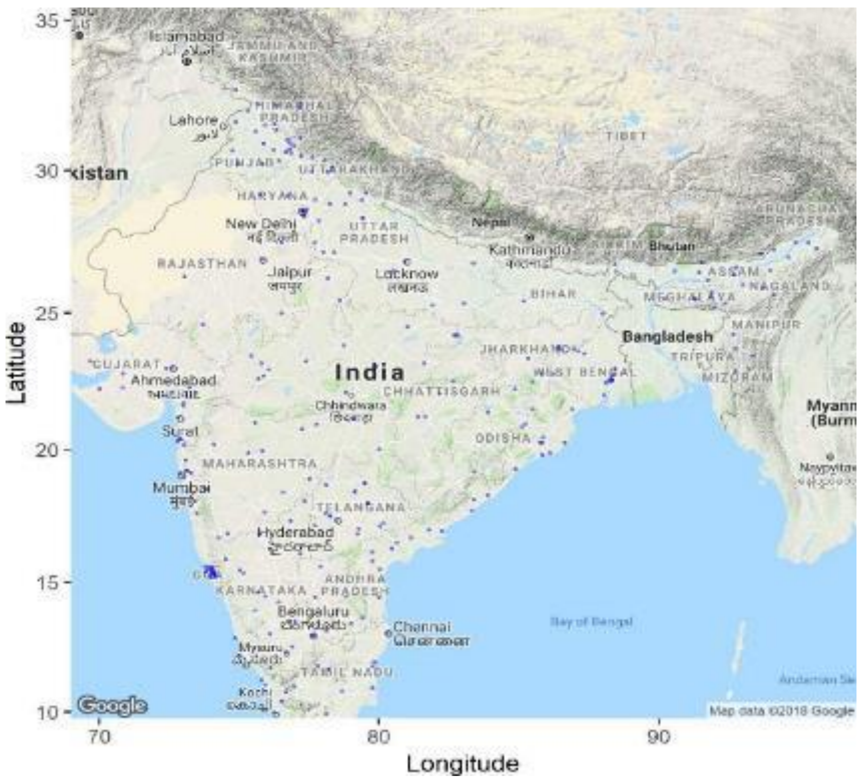
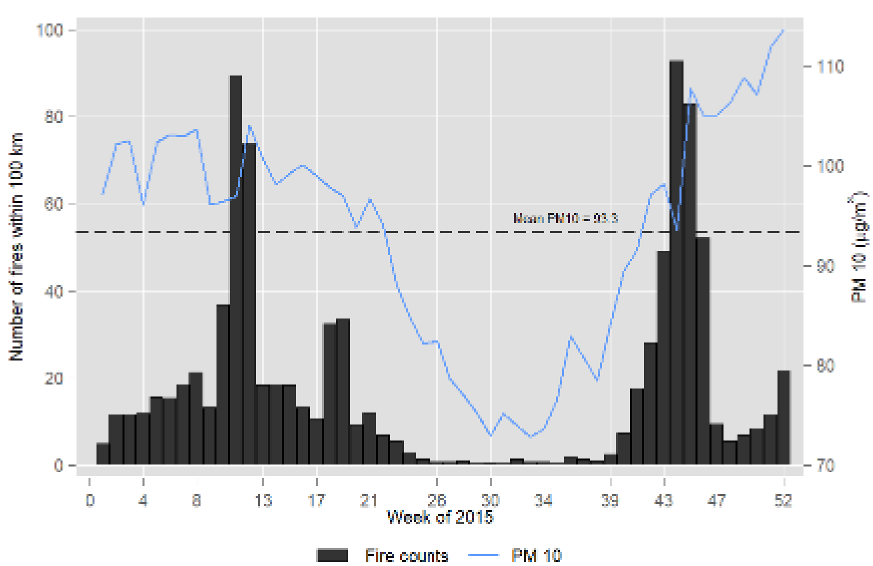


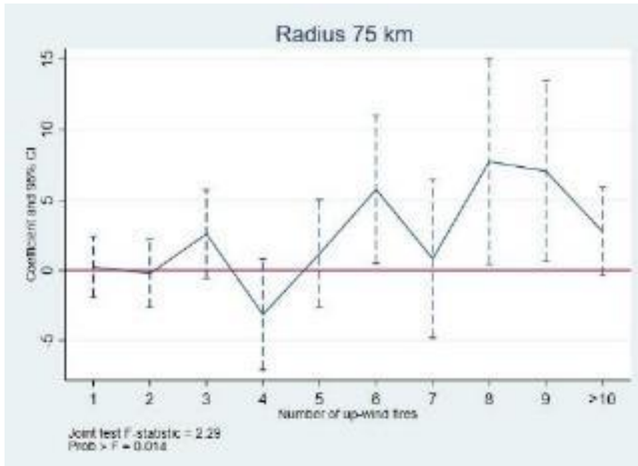

**Figure 3: Weekly variation in PM10 levels and agricultural fires within 100 km radius during 2015**



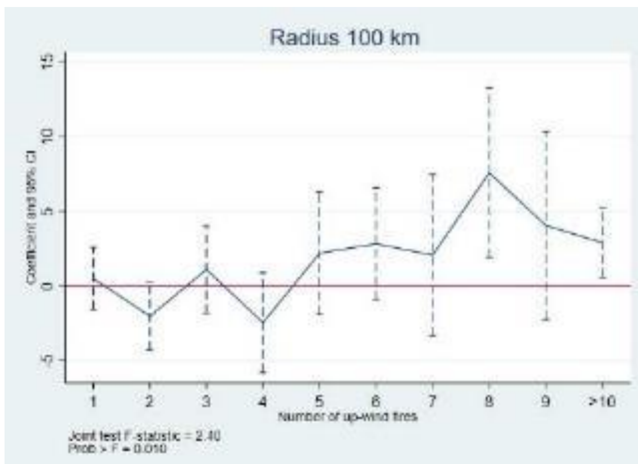

Note: Number of fires is the confidence-weighted average number of fires in the up-wind octant around each city, for each week, based on MODIS fire counts. PM10 level based on air quality meter data from a sample of 257 cities, averaged by week.

**Figure 4: Impact of up-wind fires on PM10 ($\mu$g per $m^3$): Plot of regression coefficients**

(a)



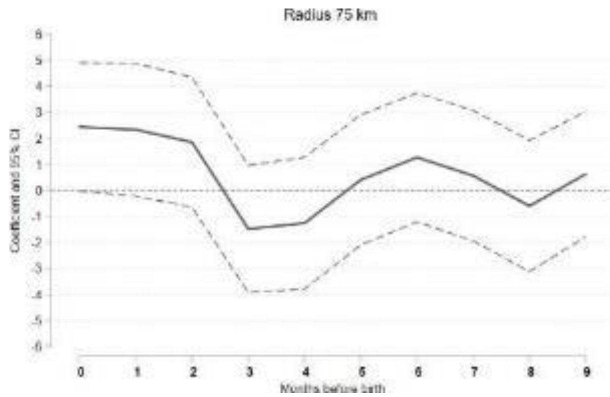

(b)



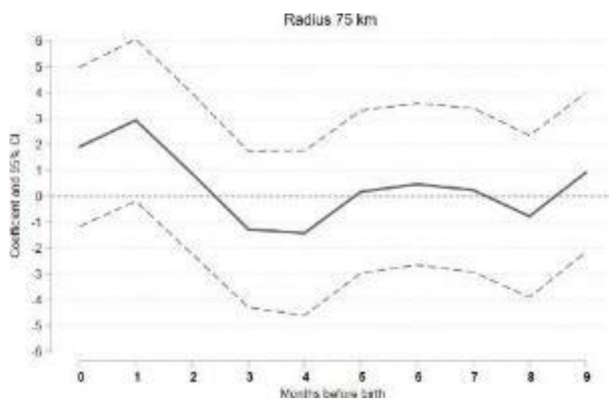

Note: Standard errors are clustered at the city level. Estimates shown from the regression of PM10 on number of up-wind fires. Reference category is zero up-wind fires. Sample is monthly air- quality meter data 2013-15 for 257 cities. All specifications include month FE, quarter-by-year FE, city-by-year FE, similar category dummies for number of fires in down-wind octant, and number of non-up/down-wind directions, and monthly mean temperature and precipitation.

**Figure 5: Impact of up-wind fires in each in utero months on mortality (deaths per 1000 births)**

**(a) Neonatal mortality**




**(b) Infant mortality**




Note: Graphs show the coefficient on variable that takes value 1 if individual was exposed to more than four fires in that month. Standard errors are clustered at the NFHS sample cluster level. Cumulative effect (sum of coefficients for each month) is 6.11(s.e = 4.28) for panel (a) and 3.99 (s.e = 5.32) for panel (b. Specification includes controls for down-wind and fires in other directions, temperature, rainfall and individual, maternal and household characteristics. All specifications also include month of birth FE, quarter-by-year FE, and cluster-by-quarter FE.

**Table 1: Descriptive statistics of air quality measures**

| Variable | (1) Above median N | (1) Above median Mean/SE | (2) Below median N | (2) Below median Mean/SE | (3) Total N | (3) Total Mean/SE | (1)-(2) t-test Difference |
|---|---|---|---|---|---|---|---|
| PM10 (μ g per $m^3$) | 2832 | 106.661 | 4611 | 91.713 | 7443 | 97.401 | 14.948*** |
| | | [3.555] | | [3.176] | | [3.094] | |
| $SO2$ (μ g per $m^3$) | 2762 | 9.398 | 4554 | 8.245 | 7316 | 8.680 | 1.153** |
| | | [0.559] | | [0.391] | | [0.433] | |
| $NO2$ (μ g per $m^3$) | 1427 | 26.814 | 2392 | 24.988 | 3819 | 25.670 | 1.825* |
| | | [1.605] | | [1.226] | | [1.238] | |

Note: The value displayed for t-tests are the differences in the means across the groups. Above and below median based on number of up-wind fires within 75 km radius. Standard errors are clustered at the city level. City-by-quarter fixed effects are included in all estimation regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

**Table 2. Impact of fires on PM10 (μg per $m^3$)**

| | (1) 75 km | (2) 100 km |
|---|---|---|
| Up-wind fires: | | |
| 1-4 | 0.0928 | -0.2679 |
| | (0.8385) | (0.8647) |
| ≥ 5 | 3.3253*** | 3.4091*** |
| | (1.1660) | (0.9516) |
| Down-wind fires: | | |
| 1-4 | 0.4591 | 1.4256 |
| | (0.8267) | (0.8649) |
| ≥ 5 | -0.2947 | 0.7947 |
| | (1.2404) | (1.1490) |
| Dep. var. mean | 98.39 | 98.39 |
| Observations | 7277 | 7277 |

Notes. Sample consists of average monthly air quality meter readings from 257 cities for 2013 - 2015. Standard errors clustered at city level (N = 257). Control variables include temperature and number of fires in non-up/down-wind direction. All specifications include month FE, quarter-by-year FE, and city-by-quarter FE. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

**Table 3: Summary of mortality rate, maternal and individual characteristics**

| | (1) | (2) | (3) | t-test | t-test |
|---|---|---|---|---|---|
| | Above median | Below median | Total | Difference | Difference |
| Variable | Mean/[SE] | Mean/[SE] | Mean/[SE] | (1)-(2) | (1)-(2) |
| Neonatal mortality (deaths per 1000 births) | 34.422 | 32.449 | 33.343 | 1.973*** | 1.973** |
| | [0.477] | [0.423] | [0.330] | | |
| Infant mortality (deaths per 1000 births) | 46.811 | 43.952 | 45.248 | 2.859*** | 2.859** |
| | [0.559] | [0.494] | [0.389] | | |
| Birth weight (g) | 2823.863 | 2812.383 | 2817.452 | 11.480*** | 11.480 |
| | [2.682] | [2.414] | [1.947] | | |
| N | 71835 | 90858 | 162693 | | |
| Birth weight (g) written record | 2820.194 | 2819.355 | 2819.726 | 0.839 | 0.839 |
| | [3.319] | [2.965] | [2.348] | | |
| N | 38321 | 48428 | 86749 | | |
| Share - low birth-weight (< 2500 g) | 0.167 | 0.168 | 0.168 | -0.001 | -0.001 |
| | [0.002] | [0.002] | [0.001] | | |
| N | 38321 | 48428 | 86749 | | |
| Total children ever born | 3.017 | 3.022 | 3.020 | -0.005 | -0.005 |
| | [0.008] | [0.007] | [0.007] | | |
| Mother's age | 29.462 | 29.238 | 29.340 | 0.224*** | 0.224*** |
| | [0.020] | [0.019] | [0.016] | | |
| Maternal education (years) | 5.629 | 5.174 | 5.381 | 0.455*** | 0.455*** |
| | [0.025] | [0.024] | [0.022] | | |
| Household head is female = 1 | 0.111 | 0.120 | 0.116 | -0.009*** | -0.009** |
| | [0.001] | [0.001] | [0.001] | | |
| Age of household head | 44.221 | 44.003 | 44.102 | 0.218*** | 0.218 |
| | [0.055] | [0.051] | [0.044] | | |
| Child is twin | 0.024 | 0.024 | 0.024 | -0.001 | -0.001 |
| | [0.001] | [0.001] | [0.000] | | |
| Sex of child (girl = 1) | 0.472 | 0.476 | 0.474 | -0.003 | -0.003 |
| | [0.002] | [0.002] | [0.001] | | |
| Wealth index category (1 – 5) | 2.684 | 2.502 | 2.585 | 0.182*** | 0.182*** |
| | [0.008] | [0.008] | [0.007] | | |
| N | 182415 | 219853 | 402268 | | |
| Clusters | 25972 | 27078 | 27997 | | |
| District-by-quarter FE | | | | No | Yes |

Note: The value displayed for t-tests are the differences in the means across the groups. Standard errors are clustered at NFHS sample cluster level. Sample consists of all births recorded from January 2007 to August 2016. Groups based on median of up-wind fires within 75 km radius during prenatal months (0 – 9 months prior to birth). The median value is zero fires. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

**Table 4. Impact on neonatal mortality**

| | Full sample | | Rural | | Urban | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | 75 km | 100 km | 75 km | 100 km | 75 km | 100 km |
| Up-wind fires: | | | | | | |
| 1 − 4 | 0.1996 | 0.9340 | 0.2224 | 1.0581 | 0.2025 | 0.6786 |
| | (1.1620) | (1.1924) | (1.2871) | (1.3258) | (2.6687) | (2.6798) |
| ≥ 5 | 2.7186* | 2.7656* | 3.2243* | 3.1026* | 0.6870 | 1.6081 |
| | (1.4890) | (1.4701) | (1.6560) | (1.6352) | (3.3919) | (3.3252) |
| Down-wind fires: | | | | | | |
| 1 − 4 | -0.4706 | -0.7158 | -0.0112 | -0.6544 | -2.5986 | -1.0263 |
| | (1.1668) | (1.1880) | (1.3029) | (1.3173) | (2.5621) | (2.7104) |
| ≥ 5 | 0.9572 | 0.0887 | 1.8796 | 1.0292 | -3.2210 | -4.1844 |
| | (1.5130) | (1.4595) | (1.6922) | (1.6220) | (3.3106) | (3.2989) |
| Dep. var. mean | 33.34 | 33.34 | 35.18 | 35.18 | 26.67 | 26.67 |
| Observations | 402268 | 402268 | 315437 | 315437 | 86831 | 86831 |

Notes. Sample consists of all births recorded from January 2007 to August 2016. Dependent variable takes value 1000 if individual died within one month of birth. Standard errors are clustered at the NFHS sample cluster level (N = 27997). Fire exposures is measured for the period 0-2 months before birth. Control variables include mother's age (5-year groups) and education category, asset-based wealth index, religion, gender of household head, gender of birth, birth order, and indicators for multiple births (twins or more). All specifications also include month of birth FE, quarter-by-year FE, and cluster-by-quarter FE. . ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

**Table 5. Impact on infant mortality**

| | Full sample | | Rural | | Urban | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | 75 km | 100 km | 75 km | 100 km | 75 km | 100 km |
| Up-wind fires: | | | | | | |
| 1 − 4 | 0.3188 | 1.0695 | 0.7750 | 1.4459 | -1.6817 | -0.3875 |
| | (1.2547) | (1.2797) | (1.4029) | (1.4286) | (2.7830) | (2.8533) |
| ≥ 5 | 3.0332* | 2.8282* | 3.6852** | 3.8750** | 0.2420 | -1.5308 |
| | (1.5922) | (1.5617) | (1.7895) | (1.7533) | (3.4878) | (3.4150) |
| Down-wind fires: | | | | | | |
| 1 − 4 | -1.5968 | -2.7453** | -1.3603 | -3.0732** | -2.7046 | -1.1969 |
| | (1.2338) | (1.2747) | (1.3934) | (1.4305) | (2.5900) | (2.7627) |
| ≥ 5 | 0.3846 | -2.3835 | 1.1973 | -2.0082 | -3.1468 | -3.9797 |
| | (1.6060) | (1.5525) | (1.8155) | (1.7439) | (3.3692) | (3.3631) |
| Dep. var. mean | 45.44 | 45.44 | 48.09 | 48.09 | 35.79 | 35.79 |
| Observations | 365589 | 365589 | 286960 | 286960 | 78629 | 78629 |

Notes. . Sample consists of all births recorded from January 2007 to November 2015 (births recorded at least 12 months before survey date to ensure full exposure). Dependent variable takes value 1000 if individual died within one year of birth. Standard errors are clustered at the NFHS sample cluster level (N = 27997). Fire exposures is measured for the period 0-2 months before birth. Control variables include mother's age (5-year groups) and education category, asset-based wealth index, religion, gender of household head, gender of birth, birth order, and indicators for multiple births (twins or more). All specifications also include month of birth FE, quarter-by-year FE, and cluster-by-quarter FE. . ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

**Table 6. Impact on under-5 mortality**

| | Full sample | | Rural | | Urban | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | 75 km | 100 km | 75 km | 100 km | 75 km | 100 km |
| Up-wind fires: | | | | | | |
| $1-4$ | 0.1422 | 0.9288 | 0.1711 | 1.1401 | 0.1294 | 0.2047 |
| | (1.2313) | (1.2557) | (1.3875) | (1.4102) | (2.6259) | (2.7217) |
| $\geq 5$ | 2.9754* | 3.1232** | 3.4927** | 3.9822** | 1.0614 | -0.2086 |
| | (1.5564) | (1.5334) | (1.7651) | (1.7356) | (3.2615) | (3.2146) |
| Down-wind fires: | | | | | | |
| $1-4$ | -1.5199 | -2.2156* | -1.1324 | -2.0886 | -3.2688 | -2.8748 |
| | (1.2144) | (1.2383) | (1.3711) | (1.3932) | (2.5626) | (2.6619) |
| $\geq 5$ | -0.4788 | -2.1927 | 0.4346 | -1.3170 | -4.3365 | -5.9506* |
| | (1.5843) | (1.5294) | (1.8036) | (1.7305) | (3.2163) | (3.2028) |
| Dep. var. mean | 50.19 | 50.19 | 53.40 | 53.40 | 38.55 | 38.55 |
| Observations | 402268 | 402268 | 315437 | 315437 | 86831 | 86831 |

Notes. Sample consists of all births recorded from January 2007 to August 2016. Dependent variable takes value 1000 if individual died within five years of birth. Standard errors are clustered at the NFHS sample cluster level (N = 27997). Fire exposures is measured for the period 0-2 months before birth. Control variables include mother's age (5-year groups) and education category, asset-based wealth index, religion, gender of household head, gender of birth, birth order, and indicators for multiple births (twins or more). All specifications also include month of birth FE, quarter-by-year FE, and cluster-by-quarter FE. . ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

**Table 7. Total number of fires and early childhood health investments**

| | Dependent variables measured per 1000 births | | | | |
|---|---|---|---|---|---|
| | Institutional medical access indicators | | Vaccinations in first one year | | |
| | (1) | (2) | (3) | (4) | (5) |
| | Delivery in hospital | Has health card | Received BCG | Received DPT | Measles |
| Number of fires | 0.0172*** | 0.0159*** | 0.00663* | 0.0191*** | 0.0551 *** |
| | (0.00511) | (0.00356) | (0.00388) | (0.00401) | (0.00388) |
| Dep. var. mean | 714.01 | 887.92 | 881.55 | 852.84 | 701.87 |
| Observations | 174053 | 165600 | 165600 | 165600 | 165600 |

Notes. Sample consists of births recorded within 5 years of survey date in the rural sample. Dependent variable takes value 1000 if answered Yes. Fire exposures is measured for the period 0-2 months before birth within 75 km radius. All specifications include state-by-year FE. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

**Table 8 Heterogenous effects across household wealth**

| | Neonatal mortality | | Infant mortality | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Rural | Urban | Rural | Urban |
| Panel A: Interaction with wealth | | | | |
| $1-4$ × Wealth index | -0.7539 | -3.1188 | -0.6401 | -2.7030 |
| | (1.3095) | (2.8622) | (1.6535) | (3.0935) |
| $\geq 5$ × Wealth index | -0.8005 | -4.8487* | -1.6822 | -4.1917* |
| | (1.3756) | (2.8653) | (1.7250) | (2.1564) |
| Panel B: Interaction with gender | | | | |
| $1-4$ × Female | -0.7332 | -0.8500 | -0.1506 | -1.8837 |
| | (2.1292) | (4.2740) | (2.6517) | (4.6739) |
| $\geq 5$ × Female | 0.1246 | -4.6452 | 0.1780 | -5.5065 |
| | (2.0274) | (3.7493) | (2.5366) | (4.0711) |
| Panel C: Interaction with birth order | | | | |
| $1-4$ × Second child | -3.1448 | -2.6948 | -4.0484 | -0.6268 |
| | (2.7156) | (4.6932) | (3.3428) | (5.2208) |
| $1-4$ × Higher order | -2.8546 | 5.7549 | -5.1222 | 6.7153 |
| | (2.7204) | (5.5727) | (3.3073) | (6.0868) |
| $\geq 5$ × Second child | -4.9141** | 0.6341 | -3.9042 | 0.3192 |
| | (2.5003) | (4.3861) | (3.0780) | (4.7917) |
| $\geq 5$ × Higher order | -0.8895 | 1.2703 | -0.5634 | 2.0317 |
| | (2.5992) | (4.9979) | (3.1808) | (5.4990) |
| Panel D: Interaction with mother working in agricultural or manual labor | | | | |
| $1-4$ × Ag. or manual labor | 4.9689 | -7.6458 | 4.7224 | 3.4835 |
| | (5.4612) | (17.8464) | (6.6071) | (20.6381) |
| $\geq 5$ × Ag. or manual labor | 6.5412 | -2.5020 | 10.6110$^{+}$ | 11.3869 |
| | (5.3385) | (14.7592) | (6.6330) | (18.4015) |
| Dep. var. mean | 35.18 | 26.67 | 48.09 | 38.55 |
| Observations | 315437 | 86831 | 286960 | 78629 |

Notes. Standard errors are clustered at the NFHS sample cluster level (N = 27997). Fire exposures is measured for the period 0-2 months before birth using a 75 km buffer. Only the interaction terms are presented for brevity. Control variables include mother's age (5-year groups) and education category, asset-based wealth index, religion, gender of household head, gender of birth, birth order, and indicators for multiple births (twins or more). All specifications also include month of birth FE, quarter-by-year FE, and cluster-by-quarter FE. ***, **, * and $^{+}$ indicate significance at the 1, 5, 10 and 15 percent critical level.

**Table 9. Placebo tests: no effect of up-wind fires in subsequent months on mortality during prior months**

| | Neonatal mortality | | Infant mortality | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | 75 km | 100 km | 75 km | 100 km |
| In-utero fires: | | | | |
| $1-4$ | 0.1618 | 0.3096 | 0.8827 | 0.9968 |
| | (1.1614) | (1.4742) | (1.1927) | (1.5033) |
| $\geq 5$ | 2.6699* | 3.0871* | 2.6776* | 2.8238 |
| | (1.4914) | (1.8728) | (1.4724) | (1.8364) |
| Fire lead 2 months: | | | | |
| $1-4$ | -0.2273 | 0.8517 | -0.8100 | -0.3073 |
| | (1.1681) | (1.4688) | (1.1366) | (1.4211) |
| $\geq 5$ | -1.6010 | 0.8691 | -0.9402 | 0.7389 |
| | (1.6487) | (2.0822) | (1.4988) | (1.8677) |
| Dep. var. mean | 33.34 | 33.21 | 48.09 | 38.55 |
| Observations | 402268 | 365589 | 402268 | 365589 |

Notes. Standard errors are clustered at the NFHS sample cluster level (N = 27997. Fires lead correspond to up-wind fires in the second and third month after birth for neonatal mortality and months 13-14 for infant mortality, respectively. Regressions include controls for down-wind fires and fires in other directions. Control variables include mother's age (5-year groups) and education category, asset-based wealth index, religion, gender of household head, gender of birth, birth order, and indicators for multiple births (twins or more). All specifications also include month of birth FE, quarter-by-year FE, and cluster-by-quarter FE. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

**Table 10. Robustness tests using alternative specifications**

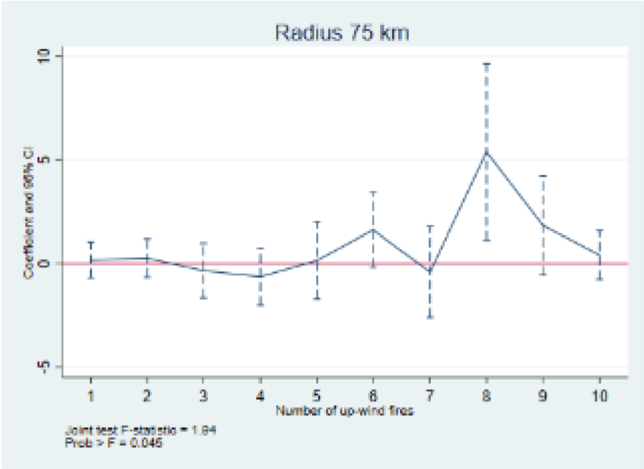
| | Neonatal mortality | | | Infant mortality | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Up-wind fires: | | | | | | |
| 1-4 | 0.1090 | 0.0900 | 0.2315 | 0.2173 | 1.0823 | 0.7750 |
| | (0.9488) | (1.5596) | (1.2273) | (1.1531) | (1.8162) | (1.5810) |
| ≥ 5 | 2.5596** | 3.5866* | 3.2401** | 3.0408** | 3.7409 | 3.6852* |
| | (1.1628) | (1.9491) | (1.5702) | (1.4019) | (2.5524) | (2.0540) |
| Down-wind fires: | | | | | | |
| 1-4 | -0.4988 | 0.0281 | 0.0087 | -1.5306 | -1.9262 | -1.3603 |
| | (0.9527) | (1.5580) | (1.2763) | (1.1370) | (2.0657) | (1.6137) |
| ≥ 5 | -0.0147 | 1.9124 | 1.8684 | 0.6816 | 1.5782 | 1.1973 |
| | (1.1820) | (2.0033) | (1.7249) | (1.4262) | (2.6090) | (2.1504) |
| Dep. var. mean | 35.18 | 41.26 | 35.18 | 48.09 | 57.02 | 48.09 |
| Observations | 315437 | 228117 | 315437 | 286960 | 201647 | 286960 |
| Fixed effects | State-quarter<br>District-year<br>Year-quarter<br>Month-of-birth | Mother<br>District-quarter<br>Year-quarter | Main spec.<br>District SE | State-quarter<br>District-year<br>Year-quarter<br>Month-of-birth | Mother<br>District-quarter<br>Year-quarter | Main spec.<br>District SE |

Notes. Standard errors are clustered at the NFHS sample cluster level, expect for columns (3) and (6). Sample consists of rural births. Fire exposures is measured for the period 0-2 months before birth using 75 km radius. All regressions control for down-wind and fires in other directions along with weather variables and other controls used in previous regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

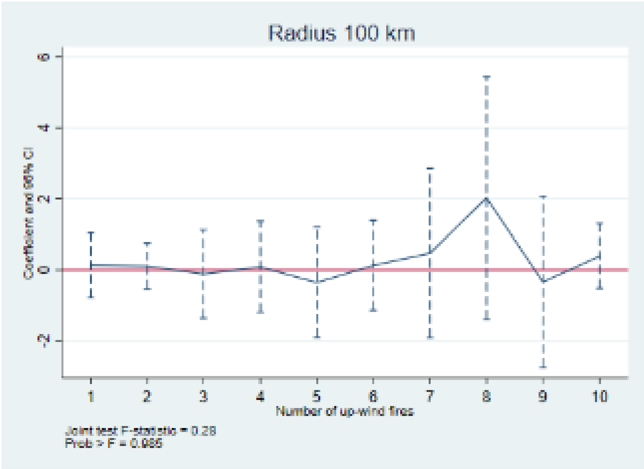
# Appendix

**Figure A1: Impact of up-wind fires on $NO_2$ ($\mu$g per $m^3$): Plot of regression coefficients**

(a)



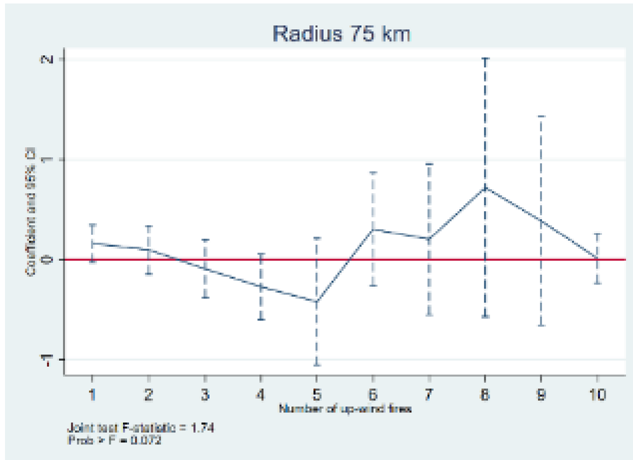

(b)



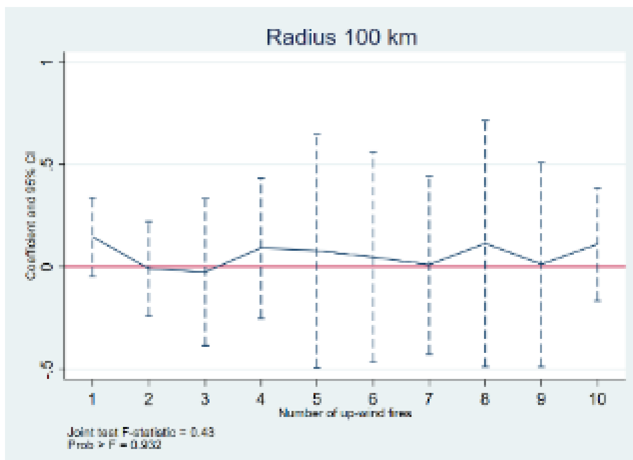

Note: Standard errors are clustered at city level. Estimates from the regression of $NO_2$ on number of up-wind fires. Reference category is zero up-wind fires. Sample is monthly air- quality meter data 2013-15 for 135 cities. All specifications include month FE, quarter-by-year FE, city-by-year FE, number of fires in non-up/down-wind directions and temperature.

**Figure A2: Impact of up-wind fires on $SO_2$ ($\mu$g per $m^3$): Plot of regression coefficients**

(a)




(b)




Note: Standard errors are clustered at city level. Estimates from the regression of $SO_2$ on number of up-wind fires. Reference category is zero up-wind fires. Sample is monthly air- quality meter data 2013-15 for 257 cities. All specifications include month FE, quarter-by-year FE, city-by-year FE, number of fires in non-up/down-wind directions and temperature.

**Figure A3: Locations of NFHS - IV sample clusters**

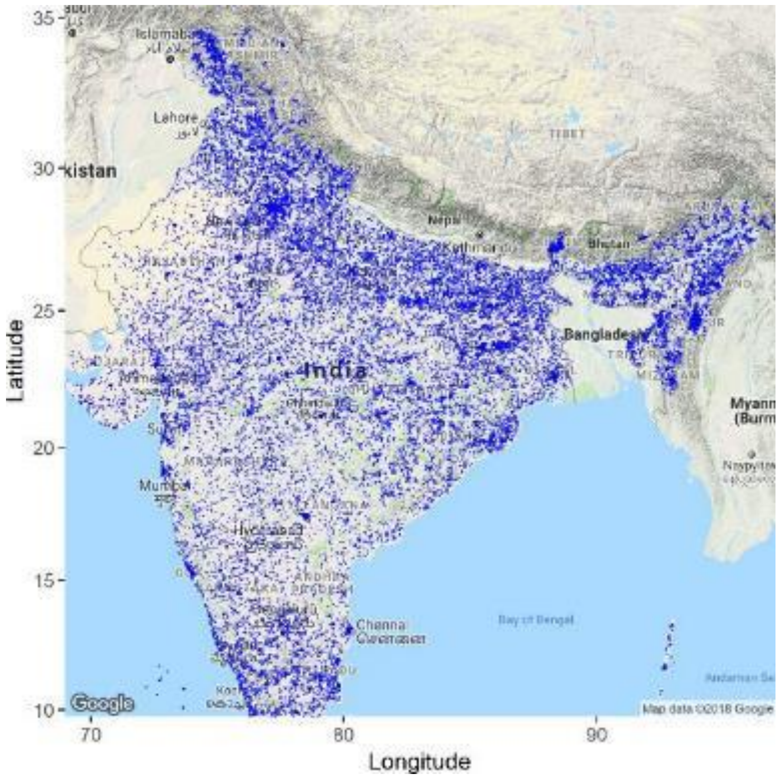


**Table A1. Fire activity within 75 km buffer**

| | Up-wind fires | | Down-wind fires | | Total fires | |
|---|---|---|---|---|---|---|
| | Panel A: Fire activity around cities with pollution measures | | | | | |
| | mean | sd | mean | sd | mean | sd |
| City-month | 5.414 | 27.725 | 6.727 | 35.250 | 49.305 | 209.115 |
| Observations | 7449 | | | | | |

Panel B: Fire activity - sample of births in NFHS 4

| | Up-wind fires | | Down-wind fires | | Total fires | |
|---|---|---|---|---|---|---|
| Months before birth | mean | sd | mean | sd | mean | sd |
| 0 | 5.157 | 23.329 | 4.838 | 21.253 | 40.091 | 133.611 |
| 1 | 5.003 | 22.891 | 4.708 | 20.749 | 38.817 | 129.697 |
| 2 | 4.853 | 22.428 | 4.545 | 20.122 | 37.718 | 126.687 |
| 3 | 4.789 | 22.126 | 4.452 | 19.711 | 37.263 | 124.777 |
| 4 | 4.707 | 21.863 | 4.381 | 19.197 | 36.681 | 122.940 |
| 5 | 4.660 | 21.729 | 4.311 | 19.034 | 36.011 | 122.001 |
| 6 | 4.618 | 21.388 | 4.276 | 19.070 | 35.771 | 121.951 |
| 7 | 4.592 | 21.491 | 4.309 | 19.187 | 35.757 | 122.101 |
| 8 | 4.751 | 22.495 | 4.300 | 19.094 | 36.130 | 123.122 |
| 9 | 4.901 | 22.510 | 4.463 | 19.854 | 37.456 | 125.971 |
| 10 | 5.054 | 23.159 | 4.802 | 21.317 | 39.440 | 132.150 |
| Observations | 407386 | | | | | |

**Table A2. Impact of fires on $SO_2$ and $NO_2$ (μg per $m^3$)**

| | $SO_2$ | | $NO_2$ | |
|---|---|---|---|---|
| | (1) 75 km | (2) 100 km | (1) 75 km | (2) 100 km |
| Up-wind fires: | | | | |
| 1-4 | 0.0729 | 0.0665 | 0.4867 | 0.0306 |
| | (0.0955) | (0.0762) | (0.3857) | (0.3869) |
| ≥ 5 | 0.3684 | 0.1485 | 1.1416 | 1.2637** |
| | (0.3066) | (0.1914) | (0.8412) | (0.5332) |
| Down-wind fires: | | | | |
| 1-4 | 0.0827 | -0.0026 | -0.3748 | -0.5540* |
| | (0.1338) | (0.0834) | (0.3757) | (0.3024) |
| ≥ 5 | -0.2581 | -0.2096 | -0.9927 | -0.4103 |
| | (0.2460) | (0.1662) | (0.6716) | (0.5193) |
| Dep. var. mean | 8.64 | 8.64 | 25.99 | 25.99 |
| Observations | 7150 | 7150 | 3689 | 3689 |

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. Sample consists of average monthly air quality meter readings from 257 cities for 2013 - 2015. Standard errors clustered at city level (N = 257). Control variables include temperature, precipitation and number of fires in non-up/down-wind direction. All specifications include month FE, quarter-by-year FE, and city-by-quarter FE.

**Table A3. Population mortality calculations**

| | | (1) NMR | (2) IMR | (3) Under-5 |
|---|---|---|---|---|
| | Effect of $\geq 5$ up-wind fires on PM10 from Table 2, Column (1) | | 3.33 $\mu g\ per\ m^3$ | |
| | Equivalent effect on PM2.5 (PM2.5 = 0.7 × PM10) | | 2.33 $\mu g\ per\ m^3$ | |
| [A] | Effect of $\geq 5$ up-wind fires on mortality rate (per 1000 births) | 2.72 | 3.03 | 2.98 |
| [B] | Sample mean mortality rate (per 1000 births) | 33.34 | 45.44 | 50.19 |
| [C] | Share of births in sample exposed to $\geq 5$ up-wind fires (%) | 0.408 | 0.414 | 0.408 |
| [D] | Mortality rate increase per 10 unit increase in PM10 $(10 * [A])/3.33$ | 8.17 | 9.10 | 8.95 |
| [E] | Mortality rate increase per 10 unit increase in PM2.5 $(10 * [A])/2.331$ | 11.67 | 13.00 | 12.78 |
| [F] | UNIGME estimate population number of deaths per annum (2006-2016 average) | 809603 | 1082837 | 1468474 |
| [G] | UNIGME mortality rate estimate (per 1000 births) (2006-2016 average) | 30.83 | 43.36 | 55.77 |
| [H] | Additional deaths due to 10 unit increase in PM10 per annum ([D] × [C])/([G] × [F]) | 87480 | 93976 | 96087 |
| [I] | Additional deaths due to 10 unit increase in PM2.5 per annum ([E] × [C])/([G] × [F]) | 124971 | 134251 | 137267 |
| [J] | GBD estimates of deaths due to ambient particulate matter pollution risk, all causes (2006-2016 average) | - | 69497 | 83766 |

Note: Population mortality number and rate from estimates generated by the UN Inter-agency Group for Child Mortality Estimation (UN IGME 2018), available at http://www.childmortality.org. Estimated mortality due to ambient particulate matter pollution based on Global Burden of Disease Study tool (GBD 2017) available from http://ghdx.healthdata.org/gbd-results-tool.

**Table A4. Impact on birth weight (in grams)**

| | Rural | | Urban | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | 75 km | 100 km | 75 km | 100 km |
| Up-wind fires: | | | | |
| 1 − 4 | 5.6848 | 4.0678 | -26.7673 | -25.8967 |
| | (15.4198) | (16.3429) | (32.9839) | (32.9888) |
| ≥ 5 | 15.9166 | 14.0556 | -13.5560 | -27.3476 |
| | (20.3011) | (19.9379) | (44.1431) | (41.4024) |
| Down-wind fires: | | | | |
| 1 − 4 | 4.0559 | -1.6982 | -21.2541 | -37.7147 |
| | (15.8001) | (16.1571) | (34.2317) | (33.8637) |
| ≥ 5 | -2.4501 | -26.1212 | -31.4194 | -37.2721 |
| | (20.1681) | (20.1027) | (45.4563) | (41.6457) |
| Dep. var. mean | 2813.67 | 2813.67 | 2837.12 | 2837.12 |
| Observations | 64441 | 64441 | 22301 | 22301 |

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Sample consists of all births recorded from February 2010 to August 2016 (five years prior to survey date). Standard errors are clustered at the NFHS sample cluster level. Control variables include mother's age (5-year groups) and education category, asset-based wealth index, religion, gender of household head, gender of birth, birth order, and indicators for multiple births (twins or more). All specifications also include month of birth FE, quarter- by-year FE, and cluster-by-quarter FE.

**Table A5 Impact on LBW (< 2500 grams)**

| | Rural | | Urban | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | 75 km | 100 km | 75 km | 100 km |
| Up-wind fires: | | | | |
| 1 − 4 | -0.0019 | -0.0048 | 0.0131 | 0.0141 |
| | (0.0102) | (0.0108) | (0.0211) | (0.0207 ) |
| ≥ 5 | -0.0191 | -0.0181 | 0.0056 | 0.0166 |
| | (0.0134) | (0.0129) | (0.0276) | (0.0261) |
| Down-wind fires: | | | | |
| 1 − 4 | -0.0004 | -0.0010 | 0.0258 | 0.0216 |
| | (0.0104) | (0.0107) | (0.0210) | (0.0217) |
| ≥ 5 | 0.0022 | 0.0170 | 0.0444 | 0.0409 |
| | (0.0137) | (0.0132) | (0.0274) | (0.0263) |
| Dep. var. mean | 0.17 | 0.17 | 0.17 | 0.17 |
| Observations | 64441 | 64441 | 22301 | 22301 |

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.002$. Sample consists of births recorded from February 2010 to August 2016 (five years prior to survey date). Dependent variable takes value 1 if birth-weight was less than 2500 grams. Standard errors are clustered at the NFHS sample cluster level. Control variables include mother's age (5-year groups) and education category, asset-based wealth index, religion, gender of household head, gender of birth, birth order, and indicators for multiple births (twins or more). All specifications also include month of birth FE, quarter- by-year FE, and cluster-by-quarter FE.