Consequences of small-scale industrial pollution: Evidence from the brick sector in Bangladesh

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Ethical considerations
A trained field team explained the study to the participants and obtained informed consent from adults aged 18 and older and informed assent from children aged 12-17. For children under 12, the primary caregiver gave informed consent and respondent on behalf of the child. The study protocol was approved by the Institutional Review Board at Stanford University (protocol #42467), as well as the Ethics Review Committee of icddr,b (the International Centre for Diarrheal Disease Research, Bangladesh).

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Abstract

Coal-fired brick kilns have spread rapidly in Bangladesh, where they are one of the largest sources of air pollution. The adverse health impacts of air pollution have been widely documented; however, there is minimal empirical evidence on the impacts of this important industry. We conducted a longitudinal study in Bangladesh to quantify the contribution of brick kilns to fine particulate matter ($PM_{2.5}$) and estimate the impact on child asthma symptoms, chronic obstructive pulmonary disease (COPD), and general respiratory symptoms. We take advantage of variation in the timing of brick production, seasonal wind direction, and household proximity to kilns to use a difference-in-difference analysis to isolate the causal effect of brick manufacturing. We find that $PM_{2.5}$ is 72.3 μg/m3 (95% CI: 10.2, 134.3) higher in areas 2 km downwind from a brick kiln during the brick production season. We also find 2.2 (95% CI: 1.2, 4.3) greater odds of COPD symptoms among adults over 40 and 4.2 (95% CI: 2.7, 6.8) greater odds of respiratory symptoms among adults over. We also found greater odds of respiratory symptoms (2.1, 95% CI: 0.7, 6.0) and asthma symptoms (2.5, 95% CI: 0.1, 96.1) among children under 5, but were underpowered in the smaller sample of children. Our results suggest that existing regulations requiring kilns to be at least 1-2 km from residential areas, schools, and health facilities are inadequate to protect population health and brick manufacturing imposes a substantial health burden on nearby communities.

Keywords

Air pollution; brick manufacturing; respiratory health; environmental policy; Bangladesh; industrial regulations

1. Introduction

Air pollution is the biggest environmental cause of disease and premature death globally and each year an estimated 4.2 million deaths are attributable to ambient air pollution (Brauer et al. 2016; Cohen et al. 2017; Landrigan et al. 2018). Air pollution in many low and middle-income countries (LMIC) has been rapidly rising due to economic development and urbanization. Given concentrations of pollutants, such as $PM_{2.5}$ are incredibly high in many LMIC, it is no surprise that 92% of air pollution related deaths occur in these countries (Cohen et al. 2017; Landrigan et al. 2018; World Health Organization 2016). In South Asia, informal brick manufacturing is one of the largest sources of air pollution (Eil et al. 2020), yet substantially less attention has been paid to the health consequences of this industry relative to other sources of air pollution, such as cookstoves (Bailis et al. 2009; Bluffstone et al. 2019; Grieshop, Marshall, and Kandlikar 2011; Hanna, Duflo, and Greenstone 2016; Kishore and Ramana 2002; Pattanayak et al. 2019) or fires and crop burning (Graff Zivin et al. 2020; Jayachandran 2009; Rangel and Vogl 2019; Tan-Soo and Pattanayak 2019).

Research on health impacts of air pollution in LMIC has been hindered by a scarcity of ground-level monitors that can be linked to individual and household level exposures. As of 2018 there were only two air pollution ground stations that reported to global databases on the entire African continent (Heft-Neal et al. 2018). While remotely sensed measures have opened opportunities for air pollution research, limitations in temporal and/or spatial resolution still prevent some applications. Consequently, the majority of evidence on health impacts of air pollution comes from high-income countries (Currie et al. 2014; Romieu et al. 2002) or is derived from modeling exercises where exposure response curves estimated from high-income countries are applied globally (Cohen et al. 2017; Lim et al. 2012). Evidence from high-income settings may not be generalizable outside of high-income settings because the relationship between health outcomes and air pollution may be nonlinear and concentrations are substantially higher in LMIC, overall morality is higher in LMIC, and health systems are generally weaker (Currie et al. 2014; Heft-Neal et al. 2018).

Quantifying the air pollution and health impacts that can be attributed to the brick industry is crucial for framing the problem for policymakers and comparing cost-effectiveness of solutions. In this paper, we overcome data limitations and empirically examining the brick manufacturing industry in the Mirzapur subdistrict of Bangladesh. We combine numerous sources of data, including an original household survey, air pollution measurements, a novel source of kiln locations, and remotely sensed meteorological data to quantify the impact of greater exposure to brick kilns on $PM_{2.5}$ concentrations and respiratory health of communities living nearby. Given that demand for bricks continues to grow (Eil et al. 2020), it is important to improve our understanding of the health consequences of this industry for Bangladesh, and across South Asia.

2. Background

2.1. Air pollution impacts

A large body of epidemiological and economics research links air pollution exposure to morbidity and mortality from chronic obstructive pulmonary disease (COPD), lung cancer, cardiovascular diseases, and overall lower life expectancy in adults (Anderson et al. 1997; Apte et al. 2018; Chen et al. 2013; Cohen et al. 2017; Dockery et al. 1993; Lim et al. 2012; C A Pope 1989; C. A. Pope 2003; C. Arden Pope III et al. 2002). $PM_{2.5}$ is particularly concerning from a health perspective because it is so small that it is inhaled deep into the lungs and can even pass into the bloodstream. Ambient air pollution exposure has also been associated with respiratory illnesses, asthma, low birthweight, pre-term birth, infant mortality, and asthma in children (Chay and Greenstone 2003; Currie et al. 2014; Currie and Neidell 2005; Currie, Neidell, and Schmieder 2009; Heft-Neal et al. 2018; Jayachandran 2009; Knittel, Miller, and Sanders 2016; Romieu et al. 2002). The relationship between air pollution and lower respiratory illnesses in children is especially important, as respiratory diseases are a leading cause of death among children under five globally (GBD 2018; Prüss-Ustün et al. 2016). This body of research documents harmful health effects of air pollution at extremely low levels, such that there may be no safe level of exposure (Di et al. 2017).

In addition to health-related impacts of air pollution, there are social and economic costs of exposure. Air pollution exposure has been associated with increased absenteeism and lower test scores in children (Currie et al. 2014; Graff Zivin et al. 2020; Graff Zivin and Neidell 2013) and reduced labor productivity (Graff Zivin and Neidell 2012), while a reduction in air pollution was found to increase labor supply in Mexico (Hanna and Oliva 2015). LMIC that experience very high air pollution also tend to have poorer educational outcomes and lower economic productivity, raising concerns of air pollution-based poverty traps.

2.2. Brick manufacturing in Bangladesh

Bangladesh has grown rapidly over the past 25 years, averaging 5.6% growth in GDP between 1990 and 2018 (The World Bank 2018). The construction industry, which accounts for 8.9% of Bangladesh's GDP, has been an important component of this economic growth (Bangladesh

Bureau of Statistics 2018; The World Bank 2016). Brick production is central to construction in Bangladesh, which lacks domestic sources of many other construction materials (Luby et al. 2015; The World Bank 2011). Consequently, traditional brick kilns have proliferated rapidly over the past few decades (Luby et al. 2015; The World Bank 2011). Approximately 7,000 brick kilns operate in Bangladesh, producing 27 billion bricks each year, contributing 1% of GDP and employing around a million people (Eil et al. 2020).

In Bangladesh, and across South Asia, bricks are primarily produced in informal, traditional-style kilns. At these kilns, workers mold bricks by hand, then fire them predominantly with coal, however wood and other biomass is occasionally used (The World Bank 2011). In Bangladesh the majority of kilns are built on low-lying land that floods during the monsoon season (Luby et al. 2015). As a result, brick production is seasonal and kilns only operate during the dry, winter months, from November to April. Traditional kilns are inefficient and emit CO_2, SO_2, CO, NO_X, $PM_{2.5}$ and black carbon into the atmosphere (Begum 2004; Begum, Hopke, and Markwitz 2013; Guttikunda, Begum, and Wadud 2013; Weyant et al. 2014). Estimates suggest that in the winter months, when brick kilns are operating, they contribute 30-50% of the $PM_{2.5}$ in Dhaka (Begum, Hopke, and Markwitz 2013; Guttikunda, Begum, and Wadud 2013), but as much as 17% of the country's total annual CO_2 emissions despite only operating for part of the year (Eil et al. 2020).

To address the air pollution and other environmental impacts of brick manufacturing, the Government of Bangladesh (GoB) has enacted a number of regulations that determine where kilns can be established, what type of fuel can be used, and the technology. For example, the Brick Manufacturing and Brick Kiln Establishment Act of 2013 restricts kilns from being built near hospitals and clinics, educational facilities, protected areas, railways, wetlands and public forests, bans the use of wood for firing, and prohibits collection of soil from agricultural land (Department of Environment 2017). However, similar to many other regulations in Bangladesh, enforcement and compliance is limited (Luby et al. 2015).

Although pollution and greenhouse gas emissions generated by brick manufacturing are well-documented (Begum 2004; Begum, Hopke, and Markwitz 2013; BUET 2007; Croitoru and Sarraf 2012; Eil et al. 2020; Gomes and Hossain 2003; Guttikunda, Begum, and Wadud 2013; Guttikunda, Goel, and Pant 2014; The World Bank 2011; Weyant et al. 2014), there is little direct, empirical evidence of the health effects of living near brick kilns. Despite their limitations, modeling studies suggest the health consequences for communities are large. Recent estimates suggest that as many as 6,000 deaths per year can be attributed to brick production in Bangladesh (Eil et al. 2020), while an estimated 4,000 premature deaths and 500,000 asthma attacks could be attributed to the brick kilns operating around Dhaka (Guttikunda and Khaliquzzaman 2014). One of the few empirical studies on health effects of brick manufacturing comes from a cross-sectional study of kiln workers in Pakistan. The authors document greater odds of chronic bronchitis and asthma among kiln workers (Shaikh et al. 2012). Although kiln workers face extreme exposures that may not be generalizable to people who simply live nearby kilns, the results are nonetheless suggestive.

3. Data and Methods

3.1. Study Setting

The study was conducted in 10 administrative unions in the Mirzapur subdistrict of Dhaka Division, located approximately 60 km northwest of Dhaka City (Figure 1). There are several large clusters of brick kilns located throughout Mirzapur, which is predominantly rural with few other sources of industrial air pollution. The locations of the unions in the study and brick kilns in Mirzapur are shown in Figure 1. These ten unions in Mirzapur were selected in order to sample participants from the study population of the Child Health Research Foundation's (CHRF) longitudinal demographic and disease surveillance study (Figure 1). Households that had not lived in the study area for at least five years or that were planning to move in the subsequent six months were excluded from this study.

The CHRF data included the GPS coordinates of *bari*s (a unit smaller than a village but typically larger than a household, containing between 1-5 households on average), which we used as a sampling frame for this study. Using these locations, we calculated the proximity of each *bari* to the closest brick kiln. Ex-ante, to classify areas as more and less exposed to kilns, we relied on the guidance included in existing government regulations, which mandates that kilns be constructed at least 1-2 km away from schools, health facilities, subdistrict centers, forests, and protected areas (Department of Environment 2017). Taking the upper bound (2 km), we stratified the *baris* by those that were more exposed to kilns (defined as at least one kiln within 2 km) and less exposed (no kiln for at least 2.5 km) and selected a random, stratified sample of baris in each union (20 exposed and 20 less exposed). Within each *bari* our team attempted to interview all households and within each household we attempted to interview all individuals. For all households and individuals, our team made three attempts.

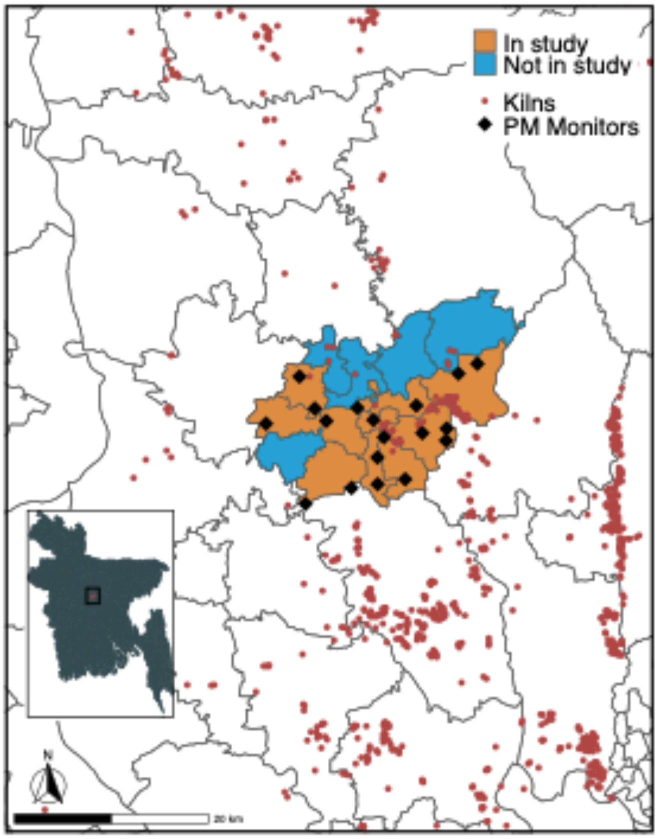

Figure 1. Map of study area in Mirzapur Upazila, Bangladesh. On the map of Mirzapur, the orange indicates administrative unions where the study was conducted, while blue indicate those unions excluded from the study because they are not included in CHRF's surveillance study. Unions are an administrative level in Bangladesh contained within sub-districts. Kilns are shown as red dots and PM monitors are displayed as black diamonds. The Mirzapur subdistrict is shown in red on the inset map of Bangladesh.

3.2. Data

3.2.1. $PM_{2.5}$ monitoring

We mapped all of the brick kilns in Bangladesh by applying a machine learning algorithm to satellite imagery and manually verified all predictions to ensure the accuracy of kiln locations (this study is described in **Authors** et al. 2021). To monitor $PM_{2.5}$, field staff deployed 18 low-cost air pollution monitors which contained a Plantower PMS A003 laser-based optical particle counter, and logged measurements of $PM_{2.5}$ every 5 minutes. The Plantower sensor is highly accurate when compared to federal reference grade monitors, although like many low-cost sensors, also sensitive to environmental conditions such as relative humidity and temperature, which we address in the analysis (Levy Zamora et al. 2019; Zusman et al. 2020). Using the same stratified sampling design, fieldworkers placed two sensors in each union, one in a *bari* that was exposed to brick kilns (2 km or closer to at least one kiln) and one in a *bari* that was less exposed to brick kilns (at least 2.5 km away from any kiln). The monitors were placed outside at a study participants' home, approximately roof-level (single level), and away from any cooking areas. Two unions received a single monitor because all *baris* in the union were classified as either exposed (Mirzapur) or unexposed (Banail) (Figure 1).

We monitored $PM_{2.5}$ continuously during the brick production season (November 2018 – March 2019) and then again during the off season (May – September 2019). The air pollution monitors logged $PM_{2.5}$ at 5-minute intervals, which we aggregated first to hourly averages and then daily averages. Any hour or day that was missing 25% or more of the expected number of observations was dropped. The resulting analytic dataset for $PM_{2.5}$ is organized at the monitor-day level, with 3,481 observations over both monitoring periods (kilns on and kilns off) across all 18 monitors (Table 1 and Table A1).

3.2.2. Individual and household survey

We conducted an individual and household questionnaire during the brick production season (November 2018 – March 2019) and returned to the same households to collect follow-up information during the brick kiln off season (May – September 2019). The household questionnaire collected information on household socioeconomic information and the individual questionnaire collected brief medical history, information about recent health symptoms and treatment, as well as standard demographic information. We also collected GPS coordinates at each household so we could construct household-level exposure to brick kilns, rather than rely on the *bari*-level GPS coordinates from the sampling frame. For children under 12, their primary caregiver answered all questions on the child's behalf, while children aged 12 and older responded themselves.

Primary health outcomes for this study include chronic obstructive pulmonary disease (COPD) symptoms for non-smoking adults 40+, asthma symptoms for children under 5, and self-reported/caregiver reported respiratory symptoms in the past four weeks for non-smoking adults (aged 18+) and children under 5. We characterized presence and frequency of COPD symptoms according to the US Preventive Services Task Force approved 5-item Lung Function Questionnaire, which has been demonstrated as an effective screening tool for COPD in outpatient settings (Guirguis-Blake et al. 2016). We classified asthma symptoms according to the International Study of Asthma and Allergies in Childhood (ISAAC) assessment tool, which is a validated multinational asthma assessment tool used extensively including by the World Health Organization (WHO) for global burden of disease asthma assessments (ISAAC 2014). We used a self-reported measure of general respiratory symptoms by asking respondents if they had any difficulty breathing, cough, or rapid breathing in the past four weeks. We also assessed severe respiratory symptoms, defined as respiratory symptoms with a fever in the past four weeks. Finally, we constructed several outcomes from the individual survey to use in a placebo analysis: whether adult respondents were aware of pollution, whether adult respondents did anything to avoid pollution, and whether adult respondents had worked on a brick kiln in the last five years.

We also collected several more objective health measurements, including spirometry, blood oxygen levels, blood carbon monoxide levels, and blood pressure, to complement the self-reported measures. However, many of the health measurements were difficult for our study participants to perform or the equipment used did not result in reliable data. Appendix B provides more details on the outcomes and survey questions they were derived from, as well as discusses the limitations of health measurements.

3.2.3. Meteorological and geographic data

We complemented our field data with additional satellite and geospatial data sets. We utilized data on daily wind speed and direction, precipitation, temperature, and humidity from the Climate Date Source ERA5 Reanalysis (Copernicus Climate Change Service (C3S) 2019) global gridded data at a spatial resolution of 0.1° latitude x 0.1° longitude. Mirzapur is covered by six grid-cells, thus we constructed daily averages of each meteorological variable for the entire region. The data on wind direction is used to define exposure to kilns, while the other meteorological data was used to calculate time-varying control variables for the air pollution models. We also utilized geospatial data on geographic factors that affect air pollution dispersion, including elevation (Jarvis et al. 2008), population density (CIESIN 2018), roads (Humanitarian Data Exchange 2018). Each of these variables was calculated at the monitor or household-level and does not vary temporally.

3.3. Exposure to Brick Kilns

To define exposure to brick kilns, we began with the 2 km cutoff that government guidelines mandate. As Panel A in Figure 2 shows, there is almost no difference in daily average $PM_{2.5}$

between monitors that were within 2 km of a kiln (exposed) and those that were not (not exposed), suggesting that distance alone is not a good proxy for exposure to air pollution generated by kilns. This descriptive plot motivates our incorporation of wind direction to better isolate exposure to air pollution from kilns from background concentrations during the firing season. As implied by classical pollution dispersion models, locations that are *downwind* from brick kilns should experience elevated $PM_{2.5}$ during the brick season that is dispersed from the kiln chimneys as they are fired.

To isolate air pollution from brick kilns, we took advantage of seasonal variation in wind direction to identify whether air pollution monitors and households were downwind from brick kilns, which has become a commonly used analytic strategy (Deryugina et al. 2019; Rangel and Vogl 2019). We examined wind rose plots that show the frequency of wind observations blowing from a given direction (Figure 3). During the brick season, the prevailing wind blows from the NW direction, while during the off season the wind blows primarily from the SE direction. Thus, we classified air pollution monitors and households that fell in the 90-degree SE sector from a kiln as downwind, while those that fall in the 90-degree NW sector were defined as upwind; any that are neither upwind nor downwind are classified as non-downwind. For sensitivity analysis, we use 45-degree sectors, although the sample size that is exposed becomes small and we lose statistical power (Table A5). After incorporating wind direction, there is a clear difference in $PM_{2.5}$ during the brick season depending on exposure to kilns, however the differences are negligible during the off season (Figure 2, Panel B).

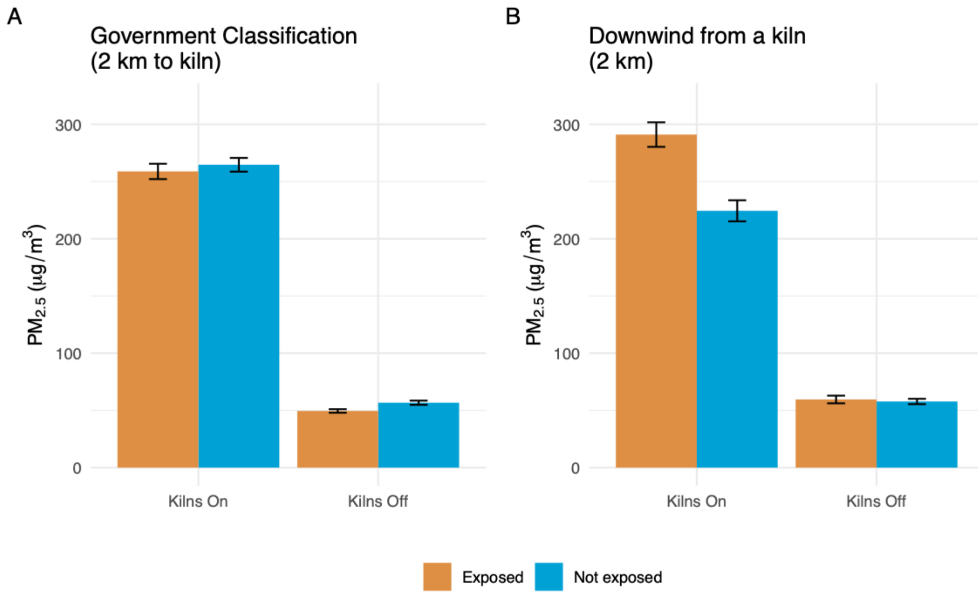

Figure 2. PM$_{2.5}$ by season and proximity to kiln within 2 km. Figure 2 plots the average PM$_{2.5}$ recorded by our monitors during the on (left) and off (right) seasons, separately for different classifications of exposure. Panel A uses the GoB's 2 km distance cutoff to determine exposure, plotting the average PM$_{2.5}$ recorded at monitors within 2 km to a kiln (exposed, orange) compared to those that were farther than 2 km (not exposed, blue). Panel B incorporates wind direction and plots the average PM$_{2.5}$ recorded at monitors that are *downwind* from a kiln within 2 km (exposed, orange) compared to those that were not downwind from any kiln for at least 8 km (not exposed, blue).

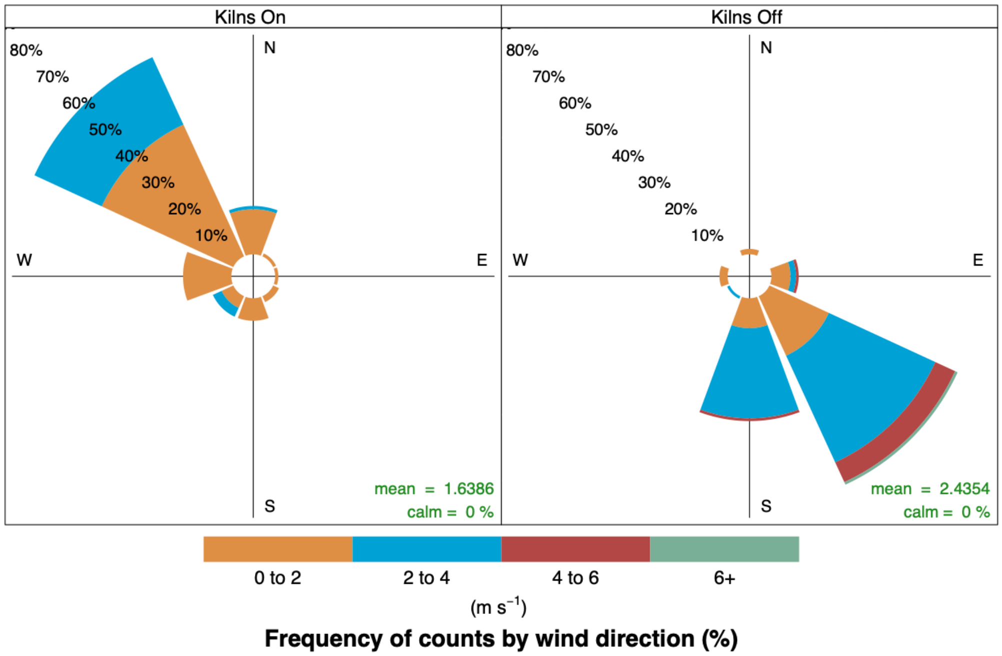

Figure 3. Seasonal variation in wind direction. Figure 3 shows a histogram (in polar coordinates) of wind direction during the brick season (left) and the off season (right), using the ERA5 wind re-analysis dataset from the Copernicus Climate Data Service.

Building off this descriptive comparison, we defined a binary measure that captures the effect of being downwind from a kiln and classifies PM monitors and households as exposed if they were downwind from at least one brick kiln within 2 km. To ensure the non-exposed areas were as far from kiln pollution as possible, we defined PM monitors and households as non-exposed if they were not downwind from any kiln for least 8 km (Equation 1). This prevents classifying households that live 2.1 km-7.9 km downwind as non-exposed. We chose the 2 km cutoff to ensure the exposure measure mapped to existing government policy as closely as possible, however we explore other distance cutoffs in our sensitivity analyses (Figure A2 and Table A2).

$$(1)\ KilnExp_i = \begin{cases} 1, & \text{if downwind from a kiln within 2 } km \\ 0, & \text{if not downwind from any kiln for at least 8 km} \end{cases}$$

Kilns are heavily clustered (Figure 1) and conditional on living downwind from a single kiln, households likely live downwind from many. To capture greater *intensity* of exposure to kilns, we also defined an inverse distance sum score:

$$(2)\ KilnExp_i = \sum_{k=1}^{n} \frac{1}{d_{i,k}}$$

where exposure for monitor or household *i* is calculated the sum of the inverse distance (*d)* between all kilns *k* and monitor or household *i*. This inverse distance weighting thus weighs kilns that are proximate more heavily. The score was calculated for all kilns that the air pollution monitors or households were *downwind* from (i.e., kilns that fall in the NW quadrant relative to the monitor or household) within 50 km.

3.4. Econometric Approach

We estimated the effect of brick kilns on each of the outcomes using a difference-in-difference approach (Equation 3). This approach compares the difference in outcomes between areas more and less exposed to kilns across the two seasons (brick firing season and off season).

$$(3)\ Y_{it} = \beta_0 + \beta_1 KilnExp_i + \beta_2 BrickSeason_t + \beta_3 KilnExp_i \times BrickSeason_t + \boldsymbol{X}\theta + \epsilon_{it}$$

where Y_{it} represents an outcome ($PM_{2.5}$, COPD symptoms, asthma symptoms, or respiratory symptoms), $KilnExp_i$ represents one of the two measures of kiln exposure defined above. This variable controls for any time-invariant, unobserved characteristics common to the exposure group, $BrickSeason_t$ is an indicator variable for data collected during the brick manufacturing season (November – March), $KilnExp_i \times BrickSeason_t$ is the difference-in-difference interaction term that captures the effect of being *more* exposed to brick kilns *during* the brick season. β_3 represents this treatment effect. $\boldsymbol{X}$ represents a vector of meteorological and geographic controls that affect air pollution dispersion including average daily rainfall, temperature, dewpoint, wind speed, average elevation, population density, distance to the closest road, distance to Mirzapur, and distance to Dhaka. Because low-cost sensors may be sensitive to environmental conditions such as humidity and temperature (Levy Zamora et al. 2019; Zusman et al. 2020), in addition to controls for daily temperature and dewpoint for the entire Mirzapur region, we also included temperature and relative humidity recorded by the sensors (as well as their interaction) in our analysis. For $PM_{2.5}$, we estimate Equation 3 using a linear model and adjusted standard errors for clustering at the monitor level.

For the health outcomes, which are all binary, we estimated Equation 3 using logistic regression, present results as odds ratios, and control for individual, household, and geographic control variables. This includes sex, age, educational attainment, a household asset index, an indicator for whether the household owns land, household size, hours of electricity, a binary variable for whether the household cooks with biomass fuel, a binary variable for smokers present in the home, elevation, population density, distance to the closest road, distance to Mirzapur City, and distance to Dhaka. For child outcomes, educational attainment is excluded due to the age of children included (under 5). We adjusted standard errors for clustering at the household level. For the health outcomes, we also included an additional term, δ_v, which represents a village fixed effect, which controls for any unobserved characteristics common to all households residing in the same village. Note that due to the smaller sample of air pollution monitors, village fixed effects cannot be included in the regressions for $PM_{2.5}$.

The sample for adults includes only non-smoking respondents, however we assessed heterogeneity by sex and smoking status (for adult health outcomes), as well as looked at severity of respiratory symptoms (symptoms with a fever). We also tested the robustness of our results by running variations of Equation 3 that included different sets of controls and fixed effects, defining binary exposure to kilns at other distance cutoffs, and exposure to kilns using 45-degree upwind sectors instead of 90-degree sectors. For the air pollution analysis, we also conducted a "leave-one-out" sensitivity test that assessed the sensitivity of the results to dropping individual monitors' data. Results for all alternative specifications and sensitivity analyses are shown in Appendix A.

This difference-in-difference approach controls for seasonal differences in the outcomes and time invariant household characteristics. The key identifying assumption for any difference-in-difference is parallel trends. In our analysis, this implies that air pollution for exposed and unexposed areas must be on similar trends during the off season. Figure 2 suggests that average $PM_{2.5}$ during the off season is similar among exposed and unexposed monitors. Although the field data we collected does not permit a comprehensive assessment of parallel trends due to the limited time span, we further assess the plausibility of parallel trends by plotting the daily average $PM_{2.5}$ over the entire study period (November 2018 – September 2019) separately for exposed and unexposed monitors (Figure A1). This figure shows how during the off season, $PM_{2.5}$ recorded by both sets of monitors is on a very similar trend but during the brick production season air pollution recorded by the exposed monitors is substantially worse relative to the unexposed monitors.

4. Results

4.1. Air Pollution ($PM_{2.5}$)

We find that $PM_{2.5}$ is higher during the brick season, a difference of 208 μg/m^3, however, more exposed monitors also experience significantly higher average $PM_{2.5}$ over the entire monitoring period (Table 1). The difference-in-difference results show that kilns increased pollution for downwind monitors (Table 3). Specifically, $PM_{2.5}$ is 72.3 μg/m^3 (95% CI: 10.2 – 134) higher at monitors that were downwind from a kiln within 2 km during the brick season. The difference-in-difference results should be interpreted as the *additional* effect of being downwind from at least one brick kiln within 2 km during the brick season, controlling for differences between more and less exposed monitors, the background seasonal trend in $PM_{2.5}$ and a range of geographic and meteorological controls that affect air pollution dispersion. We also find that increasing intensity of kiln exposure results in higher air pollution (Table 3). A one-unit increase in the inverse distance weighted sum score increases $PM_{2.5}$ during the brick season by 11.4 μg/m^3 (95% CI: 3.26 – 19.6). The average inverse sum score across the sample of PM monitors is 17 (Table 1), which implies the average monitor experiences 193.8 μg/m^3 higher $PM_{2.5}$ during the brick production season due to all of the kilns it is downwind from within 50 km.

The results are robust to defining downwind exposure to kilns at other distances (1-6 km) and were similar in magnitude to the impact at 2 km (Figure A2), although the largest effects were observed for living downwind from a kiln within 1-2 km. The difference-in-difference results were also stable across a range of specifications that controlled for differing groups of controls, monitor fixed effects, week fixed effects, monitor and week fixed effects (Figure A3), and a leave-one-out sensitivity test (Figure A4).

4.2. Health Outcomes

An initial sample of 3,552 individuals across 945 households was interviewed during the first round of data collection in the brick kiln season. During the follow up survey conducted during the off season, we reached 97.2% of the original sample, resulting in a final analytical sample of 3,451 panel individuals (2,239 over 18 and 669 under 5) across 941 households. Prevalence of COPD symptoms, asthma symptoms, and respiratory symptoms for adults and children is higher during the brick season (27%, 6%, 24%, and 36%, respectively) and among more exposed households (23%, 9%, 24%, 34%, respectively) (Table 2). Table 2 also reports summary statistics for the individual and household level covariates that do not vary over the two waves of data collection. Although individuals in exposed and not exposed households are similar on many dimensions, there are also some important differences. This is not a violation of the parallel trends assumption but does underscore the importance of controlling for these factors.

The odds of reporting COPD symptoms are 2.23 (95% CI: 1.15 – 4.33) higher among adults who lived 2 km downwind from a brick kiln during the brick season (Table 3). We find the largest effects for downwind exposure at 1-3 km; however, we do see significantly higher odds of experiencing COPD symptoms among adults living as far as 8 km downwind from a kiln (Table A2). The effect of living downwind from multiple kilns at varying distances is better captured by the inverse sum score. We find that the odds of reporting COPD symptoms are 1.08 (95% CI: 1.02 – 1.32) times higher for a one-unit increase in the inverse sum score (Table 3).

Our results show that odds of experiencing respiratory symptoms during the brick season are higher for both adults and children living downwind from kilns within 2 km (Table 3). We observed 4.25 times greater odds (95% CI: 2.7 – 6.8) of respiratory symptoms among exposed adults during the brick season. Odds of respiratory symptoms among exposed children under 5 are 2.07 (95% CI: 0.71 – 6.04) (Table 3). We also observed greater odds of respiratory symptoms with increasing intensity of kiln exposure for both adults and children (Table 3). In contrast to the binary exposure measure, when use the inverse kiln score, we find a statistically significant effect for respiratory symptoms among children, which is likely due to the larger sample size enabled by using the inverse sum score for exposure.

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Appendix A: Supplementary Tables and Figures

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List of Figures

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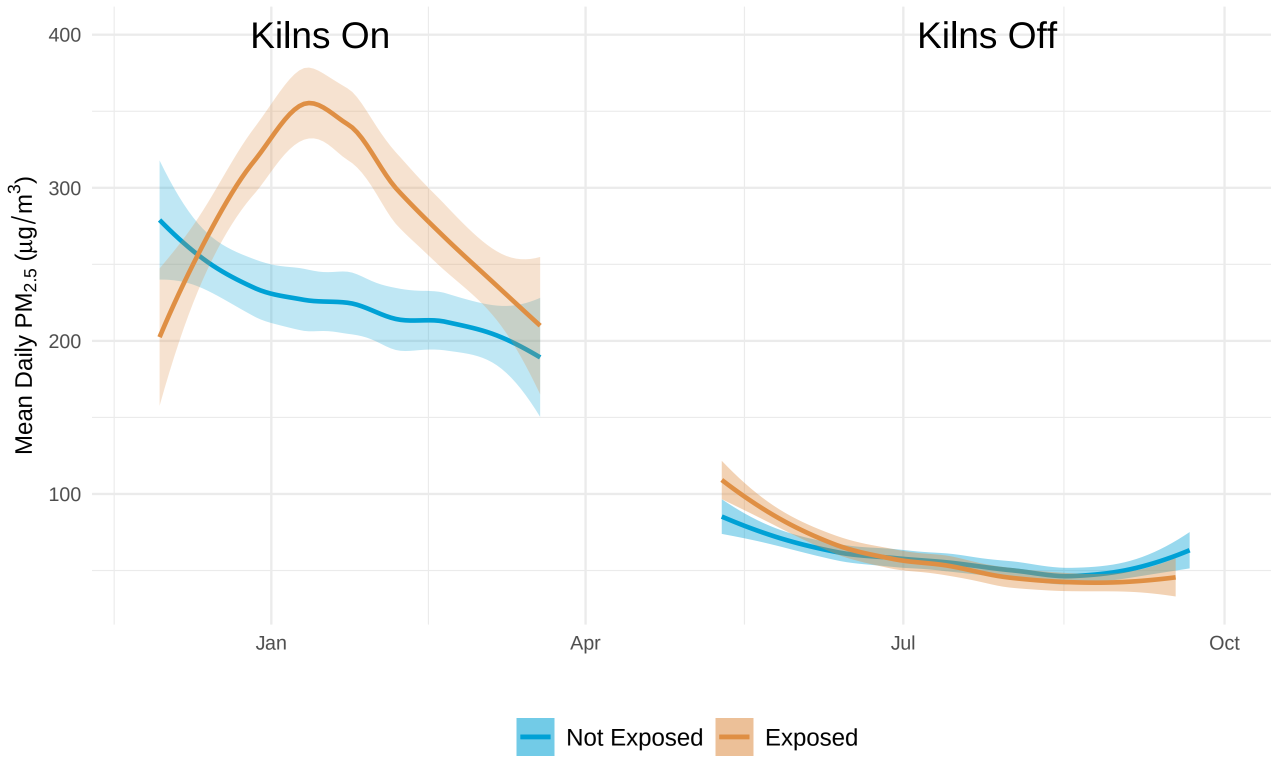
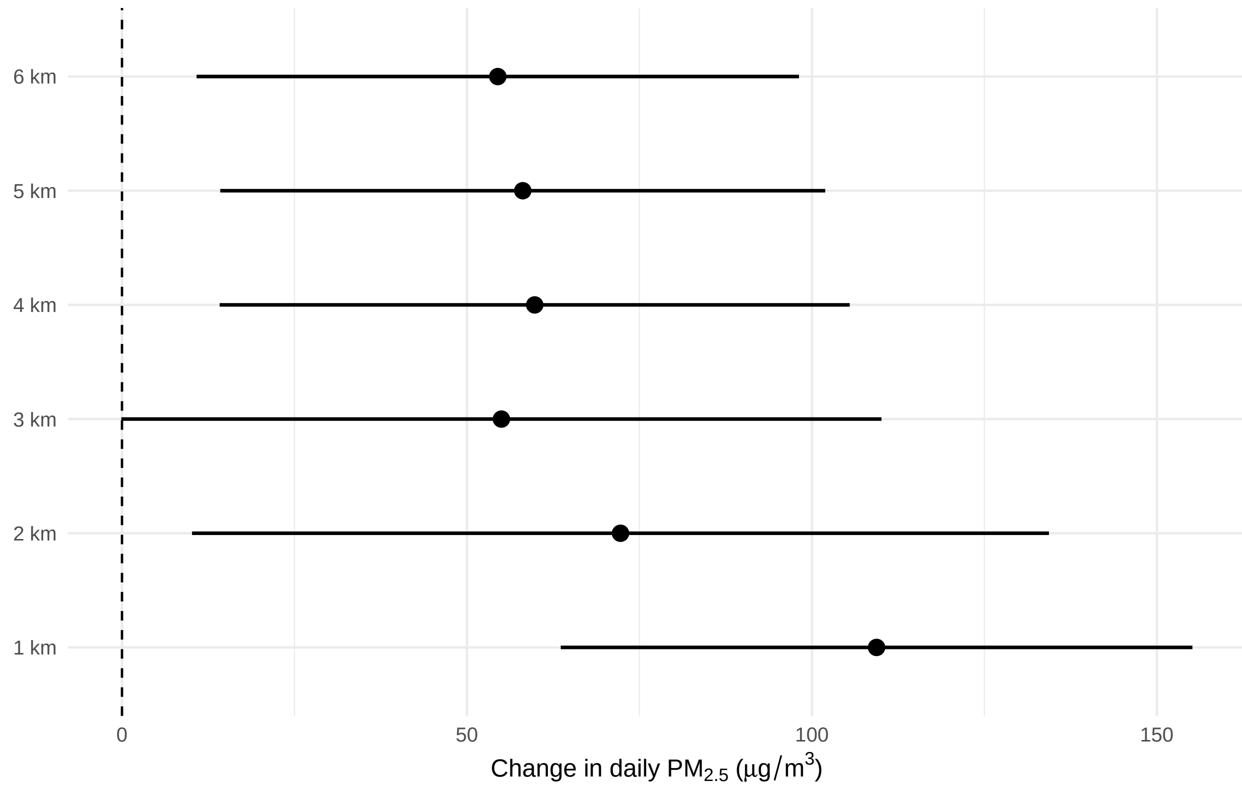
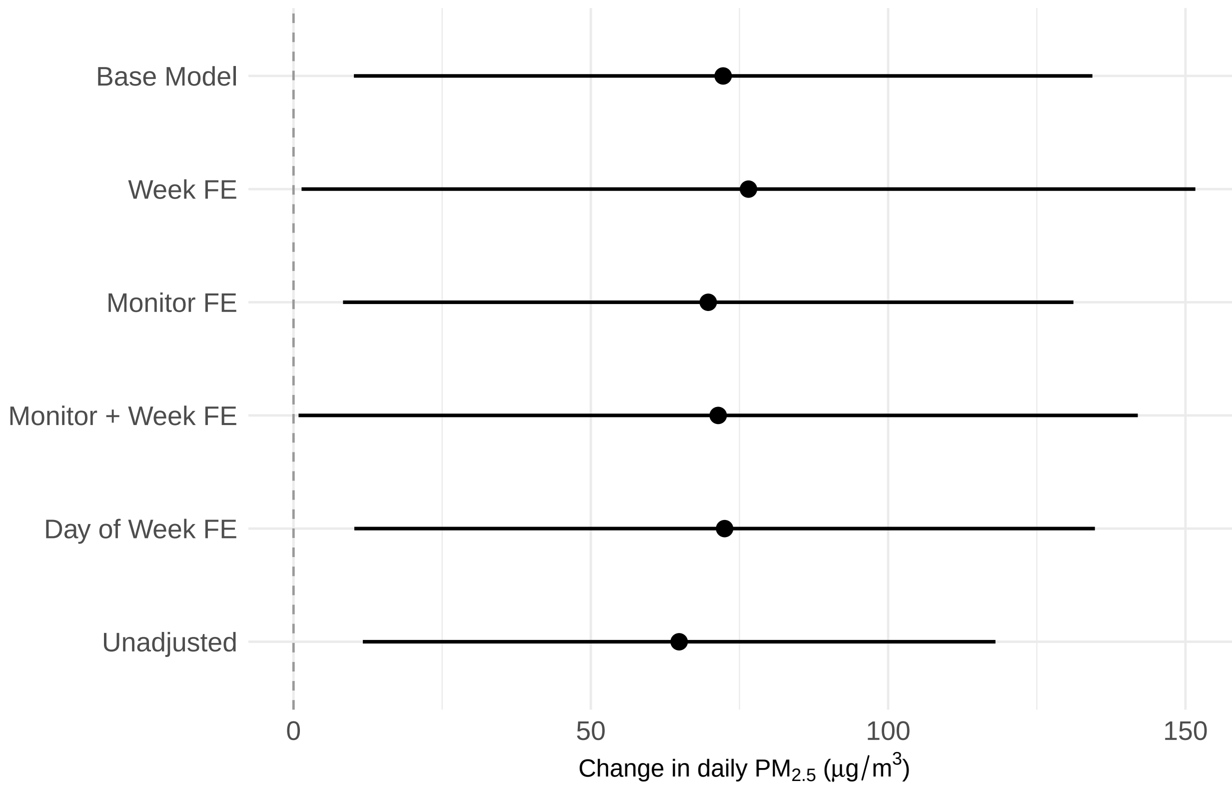
1 Supplementary Figures



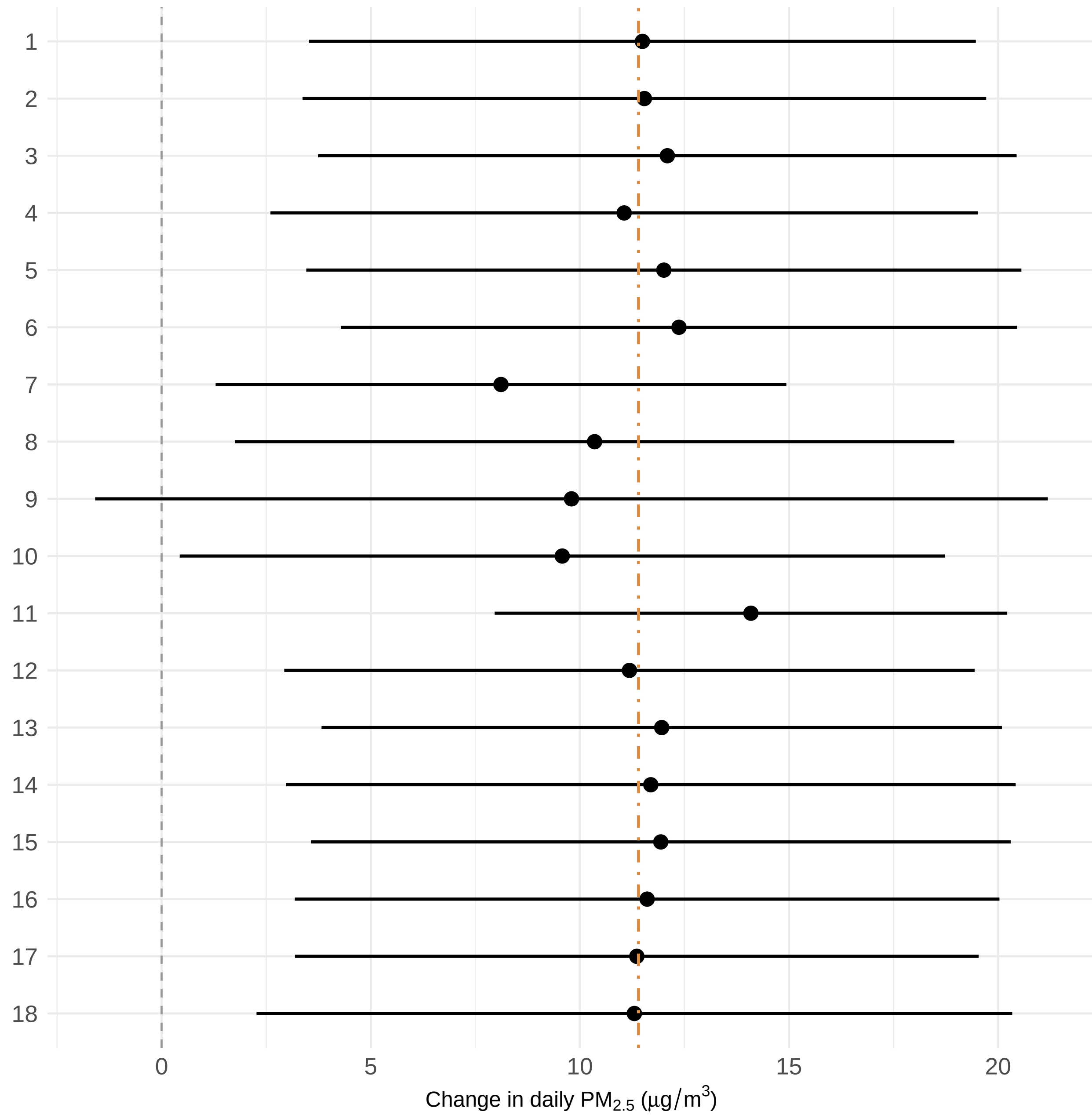
Supplementary Figure A1: PM2.5 seasonal trends by exposure to kilns. The left panel plots data collected during the brick production season and the right panel presents data collected during the off season. A lowess was fit separately for monitors that are downwind from a kiln within 2 km (exposed, orange) compared to those that were not downwind from any kiln for at least 8 km (not exposed, blue).



Supplementary Figure A2: Difference-in-difference results for $PM_{2.5}$ at other distances. Supplementary Figure A2 shows the results for the effect of being downwind from a kiln at distances 1 - 6 km. The effect at 5 km is the result reported in the main results. Each dot indicates the point estimate, lines mark the 95% confidence intervals, dashed vertical line is at 0, indicating an insignificant result at a 5% significance level.



Supplementary Figure A3: Robustness of air pollution results. Supplementary Figure A3 shows the results of robustness tests for $PM_{2.5}$. The base specification presented in Figure 3 is presented in the top row, followed by specifications with week fixed effects, monitor fixed effects, monitor and week fixed effects, day of the week fixed effects, and an unadjusted model in the bottom row. Each dot indicates the point estimate, lines mark the 95% confidence intervals, dashed vertical line is at 0, indicating an insignificant result at a 5% significance level.



Supplementary Figure A4: Leave-one-out Sensitivity Test. Supplementary Figure A4 presents the results for running the difference-in-difference (using the inverse sum score for exposure) 18 times, dropping all the observations from one monitor each time, to ensure the results are not sensitive to any particular monitor. Each row presents the result for dropping that monitor (ie. the first row presents the results dropping all observations from monitor #1, etc.). The orange, dashed vertical line marks the base result, which uses all 18 monitors, shown in Table 3. The grey dashed vertical line at 0, indicating an insignificant result at a 5% significance level.

2 Supplementary Tables

Supplementary Table A1: PM Monitor Statistics

Union	On Season $PM_{2.5}$	Off Season $PM_{2.5}$	Closest (km)	# of kilns downwind from within: 2 km	5 km	10 km
Gorai	328.9	65.1	0.7	2	10	12
Gorai	301.9	50.0	3.1	0	15	25
Bahuria	299.9	65.6	1.0	2	3	6
Lotifpur	295.3	58.1	4.3	0	1	4
Bhatgram	285.3	44.3	3.5	0	1	5
Bhatgram	274.5	44.4	4.9	0	1	1
Jamurki	272.8	54.5	3.4	0	1	1
Bhaora	259.2	33.3	5.4	0	0	2
Ajgana	258.9	50.4	1.3	2	4	6
Banail	258.3	47.9	10.1	0	0	0
Bhaora	256.3	78.4	8.1	0	0	1
Ajgana	253.1	51.6	2.7	0	3	5
Jamurki	252.1	49.9	10.7	0	0	0
Uarsi	251.1	83.0	12.3	0	0	0
Bahuria	244.7	47.4	3.2	0	9	18
Mirzapur	242.1	40.1	5.1	0	0	5
Uarsi	145.4	32.1	14.7	0	0	0
Lotifpur		46.5	2.1	0	14	19

Notes: Supplementary Table A1 presents monitor-level summary statistics for the 18 PM monitors deployed in the study area. The first column reports the brick season average $PM_{2.5}$, the second column reports the off season average $PM_{2.5}$, the third column presents the distance to the closest upwind kiln (in km), and the final three columns report the number of kilns each monitor is downwind from within 2 km, 5 km, and 10 km, respectively. Note that due to hardware malfunctions we were unable to place the second monitor in Lotifpur during the brick season, thus this entry is blank.

Supplementary Table A2: Difference-in-difference results for health outcomes at other distances

Downwind	COPD (Adults 40+)		Respiratory Symptoms (Adults 18+)		Respiratory Symptoms (Children ≤ 5)		Asthma (Children ≤ 5)	
from kiln in:	Odds Ratio (95% CI)	N	Odds Ratio (95% CI)	N	Odds Ratio (95% CI)	N	Odds Ratio (95% CI)	N
1 km	3.42 (1.63, 7.17)	501	5 (2.65, 9.44)	1,126	1.14 (0.46, 2.82)	180	0 (0, NA)	51
2 km	2.23 (1.15, 4.33)	659	4.25 (2.67, 6.76)	1,423	2.07 (0.71, 6.04)	241	2.49 (0.06, 96.13)	71
3 km	2.21 (1.21, 4.03)	768	3.28 (2.05, 5.26)	1,642	2.3 (0.96, 5.53)	263	1.07 (0.04, 26.52)	83
4 km	2.01 (1.31, 3.08)	1,182	2.54 (1.5, 4.31)	2,491	1.96 (0.91, 4.2)	427	2.78 (0.13, 61.5)	165
5 km	2.09 (1.22, 3.56)	1,367	2.68 (1.73, 4.17)	2,843	2 (0.85, 4.71)	493	2.98 (0.12, 73.11)	196
6 km	2.21 (1.4, 3.49)	1,598	2.46 (1.62, 3.75)	3,246	2.03 (0.87, 4.76)	558	3.19 (0.15, 69.59)	234
7 km	2.13 (1.27, 3.55)	1,702	2.39 (1.55, 3.69)	3,423	1.74 (0.79, 3.83)	585	3.23 (0.14, 72.24)	254
8 km	2.03 (1.25, 3.28)	1,783	2.37 (1.56, 3.61)	3,582	1.69 (0.76, 3.75)	615	3.08 (0.15, 64.4)	278

Notes: This table presents difference-in-difference using the binary kiln exposure defined at distances 1-8 km. All four of the health outcomes (COPD for adults 40+, self-reported respiratory symptoms in the past 4 weeks for adults 18+, asthma for children ≤ 5, and caregiver-reported respiratory symptoms in the past 4 weeks for children ≤ 5) were estimated using logistic regression and odds ratios are reported, with 95% confidence intervals shown in parentheses. Controls for health outcomes include sex, age, educational attainment (adults only), a household asset index, an indicator for whether the household owns land, an indicator for whether the household is constructed from quality materials, household size, hours of electricity, a binary variable for whether the household cooks with biomass fuel, a binary variable for smokers present in the home, whether the individual is aware of pollution (adults only), and whether the individual has worked on a brick kiln (adults only), average elevation, population density, distance to the closest road, distance to Mirzapur City, and distance to Dhaka City and village fixed effects.

Supplementary Table A3: Alternative specifications for health outcomes

	COPD (Adults 40+)		Respiratory Symptoms (Adults 18+)		Respiratory Symptoms (Children ≤ 5)		Asthma (Children ≤ 5)	
	Odds Ratio (95% CI)	N	Odds Ratio (95% CI)	N	Odds Ratio (95% CI)	N	Odds Ratio (95% CI)	N
Downwind from kiln in 2 km								
Unadjusted	1.98 (1.01, 3.86)	822	3.81 (2.04, 7.09)	1,459	1.32 (0.43, 4.05)	257	0.94 (0.08, 11.36)	257
Demographic Controls	2.22 (0.97, 5.07)	822	3.88 (2.07, 7.26)	1,459	1.25 (0.4, 3.92)	257	0.99 (0.08, 11.9)	257
SES Controls	2.01 (1.02, 3.95)	822	3.82 (2.05, 7.12)	1,459	1.38 (0.43, 4.41)	257	0.94 (0.08, 11.53)	257
Geographic Controls	1.99 (1, 3.96)	822	3.83 (2.05, 7.15)	1,459	1.43 (0.45, 4.57)	257	1.05 (0.08, 13.39)	257
Pollution Confounders	1.96 (0.99, 3.85)	822	3.78 (2.02, 7.07)	1,459	1.31 (0.43, 4.04)	257	0.98 (0.08, 12.36)	257
All Controls	2.43 (0.96, 6.14)	822	3.92 (2.07, 7.43)	1,459	1.45 (0.43, 4.91)	257	1.04 (0.07, 16.49)	257
Village FE	2.23 (1.15, 4.33)	659	4.25 (2.67, 6.76)	1,423	2.07 (0.71, 6.04)	241	2.49 (0.06, 96.13)	71
Smokers Included	2.2 (0.93, 5.19)	997	3.34 (2.25, 4.96)	1,760				
Male	1.23 (0.31, 4.89)	229	3.02 (0.9, 10.19)	390				
Female	8.35 (1.43, 48.78)	592	5.09 (2.46, 10.55)	1,068				
Inverse Sum Score								
Unadjusted	1.06 (0.99, 1.14)	2,025	1.13 (1.05, 1.23)	3,652	1.09 (0.96, 1.24)	669	0.98 (0.81, 1.19)	669
Demographic Controls	1.09 (0.99, 1.19)	2,025	1.14 (1.05, 1.23)	3,652	1.09 (0.96, 1.24)	669	0.98 (0.81, 1.19)	669
SES Controls	1.06 (0.99, 1.14)	2,025	1.14 (1.05, 1.23)	3,652	1.09 (0.96, 1.25)	669	0.98 (0.8, 1.2)	669
Geographic Controls	1.07 (0.99, 1.15)	2,025	1.14 (1.05, 1.24)	3,652	1.12 (0.96, 1.29)	669	0.97 (0.74, 1.29)	669
Pollution Confounders	1.06 (0.98, 1.14)	2,025	1.13 (1.05, 1.23)	3,652	1.09 (0.96, 1.24)	669	0.97 (0.79, 1.19)	669
All Controls	1.09 (0.98, 1.22)	2,025	1.14 (1.05, 1.24)	3,652	1.11 (0.96, 1.3)	669	0.97 (0.73, 1.29)	669
Village FE	1.08 (1.02, 1.14)	1,783	1.17 (1.03, 1.33)	3,582	1.14 (1, 1.3)	615	1.01 (0.79, 1.29)	278
Smokers Included	1.07 (0.97, 1.17)	2,475	1.13 (1.07, 1.2)	4,430				
Male	1.08 (0.92, 1.27)	548	1.07 (0.93, 1.23)	973				
Female	1.16 (0.97, 1.38)	1,475	1.17 (1.05, 1.31)	2,677				

Notes: This table presents difference-in-difference using both the binary kiln exposure (downwind from a kiln within 2 km), shown in the top section, and the inverse sum score, shown in the bottom section with increasing sets of controls. All four of the health outcomes (COPD for adults 40+, self-reported respiratory symptoms in the past 4 weeks for adults 18+, asthma for children ≤ 5, and caregiver-reported respiratory symptoms in the past 4 weeks for children ≤ 5) were estimated using logistic regression and odds ratios are reported, with 95% confidence intervals shown in parentheses. Demographic controls include sex, age, educational attainment (adults only), and household size. Socioeconomic (SES) controls include a household asset index, an indicator for whether the household owns land, an indicator for whether the household is constructed from quality materials, and hours of electricity. Geographic controls include average elevation and population density in 10 km buffer zone around each household, distance to the closest road, distance to Mirzapur City, and distance to Dhaka City. Pollution confounder controls include a binary variable for whether the household cooks with biomass fuel, a binary variable for smokers present in the home, whether the individual is aware of pollution (adults only), and whether the individual has worked on a brick kiln (adults only). We also present results for models that include all controls, all controls and village fixed effects, include smokers (with all controls and village fixed effects), and all controls split by sex. Because the sample of children under 5 is already small, we cannot estimate by sex-specific models.

Supplementary Table A4: Difference-in-difference results for severe respiratory symptoms

	Downwind from kiln (2 km)		Inverse Sum Score	
	Odds Ratio (95% CI)	N	Odds Ratio (95% CI)	N
Severe Respiratory Symptoms (Adults 18+)				
Unadjusted	4.46 (1.95, 10.17)	1,459	1.13 (1.02, 1.25)	3,652
All Controls + Village FE	4.97 (2.74, 9.02)	1,347	1.18 (0.96, 1.46)	3,446
Severe Respiratory Symptoms (Children $\leq$ 5)				
Unadjusted	0.67 (0.18, 2.49)	257	1.01 (0.88, 1.15)	669
All Controls + Village FE	0.74 (0.41, 1.32)	201	1.01 (0.92, 1.11)	558

Notes: This table presents difference-in-difference using both the binary kiln exposure (downwind from a kiln within 2 km), shown in the first two columns, and the inverse sum score, shown in the second two columns for severe respiratory symptoms (defined as respiratory symptoms in the past four weeks with a fever). These models were estimated using logistic regression and odds ratios are reported, with 95% confidence intervals shown in parentheses. Controls for health outcomes include sex, age, educational attainment (adults only), a household asset index, an indicator for whether the household owns land, an indicator for whether the household is constructed from quality materials, household size, hours of electricity, a binary variable for whether the household cooks with biomass fuel, a binary variable for smokers present in the home, whether the individual is aware of pollution (adults only), and whether the individual has worked on a brick kiln (adults only), average elevation, population density, distance to the closest road, distance to Mirzapur City, and distance to Dhaka City.

Supplementary Table A5: Difference-in-difference results for primary outcomes using 45-degree sectors for downwind

	Downwind from kiln (2 km)		Inverse Sum Score	
	Coefficient (95% CI)	N	Coefficient (95% CI)	N
$PM_{2.5}$				
Unadjusted	40.95 (-9.65, 91.54)	1,954	9.81 (-2.59, 22.2)	3,481
All Controls	59.2 (-7.45, 125.86)	1,954	12.5 (-1.46, 26.46)	3,481
COPD (Adults 40+)				
Unadjusted	1.95 (0.94, 4.06)	1,197	1.12 (1, 1.26)	2,025
All Controls	2.91 (0.9, 9.44)	801	1.12 (0.91, 1.37)	1,433
Respiratory Symptoms (Adults 18+)				
Unadjusted	2.31 (1.3, 4.1)	2,120	1.15 (1.02, 1.29)	3,652
All Controls	2.31 (1.2, 4.44)	1,589	1.11 (0.97, 1.26)	2,855
Respiratory Symptoms (Children $\leq$ 5)				
Unadjusted	1.11 (0.39, 3.13)	378	1.11 (0.9, 1.37)	669
All Controls	1.14 (0.37, 3.53)	378	1.11 (0.88, 1.41)	669
Asthma (Children $\leq$ 5)				
Unadjusted	0.49 (0.05, 5.12)	378	0.96 (0.68, 1.35)	669
All Controls	0.56 (0.05, 6.05)	378	0.94 (0.62, 1.43)	669

Notes: This table presents difference-in-difference using both the binary kiln exposure (downwind from a kiln within 2 km), shown in the first two columns, and the inverse sum score, shown in the second two columns, where downwind was defined as the 45-degree sector SE of the kiln instead of 90-degree sector (as in Table 3).

Consequences of small-scale industrial pollution: Evidence from the brick sector in Bangladesh

Appendix B: Data and Measures

September 7, 2021

1 Survey questions and measures

1.1 COPD symptoms

We characterized presence and frequency of COPD symptoms according to the US Preventive Services Task Force approved 5-item Lung Function Questionnaire, which has been demonstrated as an effective screening tool for COPD in outpatient settings (Guirguis-Blake et al. 2016). These questions were only asked of adults aged 40 and over. Questions included: "How often do you cough up mucus?", "How often does your chest sound noisy (wheezy, whistling, rattling) when you breathe?", "How often do you experience shortness of breath during physical activity (walking up a flight of stairs or walking up an incline without stopping to rest)?", "How many years have you smoked?", and "What is your age?". Each question is scored on a 5-point scale, with answers associated with greater COPD risk given a lower score. For example, never coughing up mucus is given a score of 5, while coughing up mucus "very often" receives a score of 1. A total score of <18 is considered at risk of COPD.

1.2 Asthma symptoms

We assessed asthma symptoms using the International Study of Asthma and Allergies in Childhood (ISAAC) assessment tool, which was included as a survey module for all participants aged 18 and under. The ISAAC is a validated multinational asthma assessment tool used extensively including by the World Health Organization (WHO) for global burden of disease asthma assessments (ISAAC 2014). The key question used for assessing asthma symptom prevalence was: "Have you (has your child) had wheezing or whistling in the chest in the last 12 months?". For children under 12, their primary caregiver answered all questions, including the ISAAC questionnaire and respiratory symptoms on the child's behalf. We found extremely low prevalence of asthma in our sample (4% of children under 5, see Table 1 in the main manuscript), which may have caused our results to be underpowered. The low prevalence could be due to the unfamiliarity with asthmatic symptoms among our study population. Although trained fieldworkers showed respondents a video with different examples of wheezing, the unfamiliarity may have resulted in an underestimate. However, the low asthma prevalence we detected is in line with other studies in South Asia (Pearce et al. 2007). Additionally, due to smaller sample sizes of children under 5, the results for asthma and respiratory symptoms may be underpowered in general.

1.3 Respiratory symptoms

We used a self-reported measure of general respiratory symptoms by asking respondents if they had any difficulty breathing, cough or rapid breathing in the past four weeks. We also assessed severity of respiratory symptoms, defined as respiratory symptoms with a fever in the past four weeks. These questions were asked of respondents of all ages, and for children under 12, primary caregivers responded on their behalf.

1.4 Alternative hypotheses

We assessed three outcomes that reflect alternative hypotheses: whether adult respondents thought there was pollution in their village, whether adult respondents did anything to avoid pollution, and whether adult respondents had worked on a brick kiln in the last five years. These questions were only asked of adults aged 18 and over. Whether respondents did anything to avoid pollution was only asked of respondents who indicated they were aware of pollution in their village.

2 Additional Health Measurements

We also collected oxygen and carboxyhemoglobin saturation levels from all study participants. For adults aged 18 and over we also measured blood pressure to investigate the link between air pollution exposure and cardiovascular disease. Finally, for adults aged 40 and over we measured lung function by spirometry using forced expiratory volume in 1 second (FEV1) and forced expiratory volume in 6 seconds (FEV6). Although we did spirometry for adults over 40 to obtain a more objective measure of COPD, the test proved extremely difficult for participants to perform well. Spirometry, in particular, is notoriously difficult, even in clinical settings and particularly so for people with obstructed airways (Bellia et al. 2008; Allen et al. 2008; Arne et al. 2010). Despite collecting three spirometry trials from each adult, the majority of the data was not high quality and was not consistent with the quality standards laid out in the American Thoracic Society (ATS) and European Respiratory Society recommendations (Miller 2005). Prevalence of COPD defined by the spirometry measurement was also very low, making estimation difficult due to low statistical power. Ultimately, we preferred the questionnaire-based tool for COPD as our primary outcome, which has been demonstrated to be a good screening tool (Guirguis-Blake et al. 2016), and the results should be interpreted as suggestive, but not indicative, of COPD exacerbations.

We found no relationship between exposure to air pollution from brick kilns during the brick season on blood pressure, hypertension, blood carbon monoxide levels (adults or children) or blood oxygen levels (adults or children) (Figures B1 and B2, Table B1). Although particulate matter has been well-established as a risk factor for cardiovascular disease (Cohen et al. 2017), there remains substantial uncertainty over the role of PM on blood pressure as an explanatory pathway (Shanley et al. 2015).) It is perhaps unsurprising we did not identify a strong relationship, given the many open questions over the non-linearities in dose-response between PM2.5 and blood pressure and differences between short and long-term exposure (Arku et al. 2020; Yang et al. 2018). However, we did find a striking seasonal pattern in hypertension prevalence with more than double the rate during the brick season (Figure B1). Future work should look into this seasonal pattern of blood pressure results. Given the inconsistencies with these measurements, we excluded these data from the primary analysis, but report them in here.

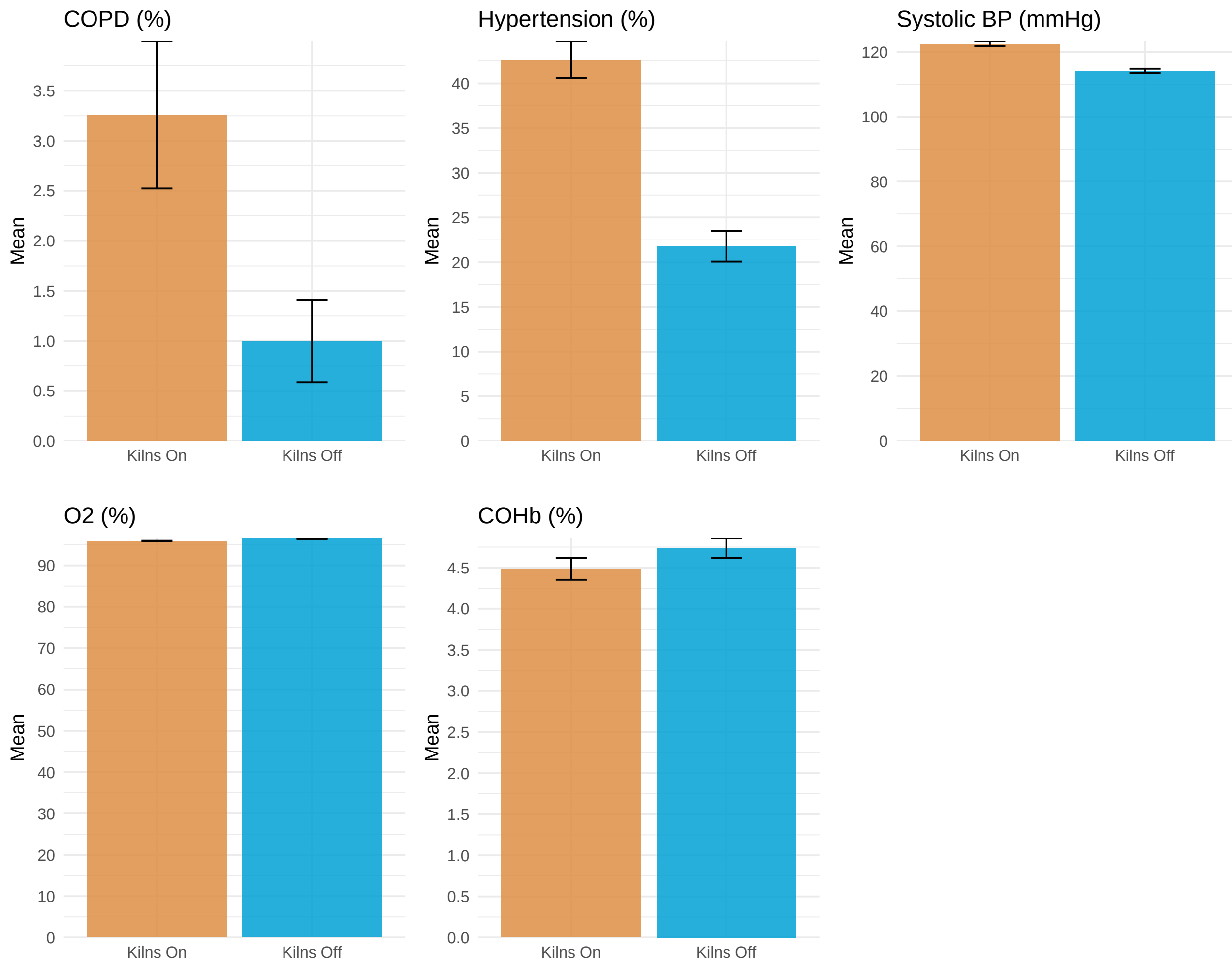


Figure B1: Descriptive plot of other adult health outcomes by season. Supplementary Figure B1 presents the average of each of the other health outcomes for adults in the brick season (orange) and the off season (blue). The black bars indicate± 1.96 standard deviations around the mean.

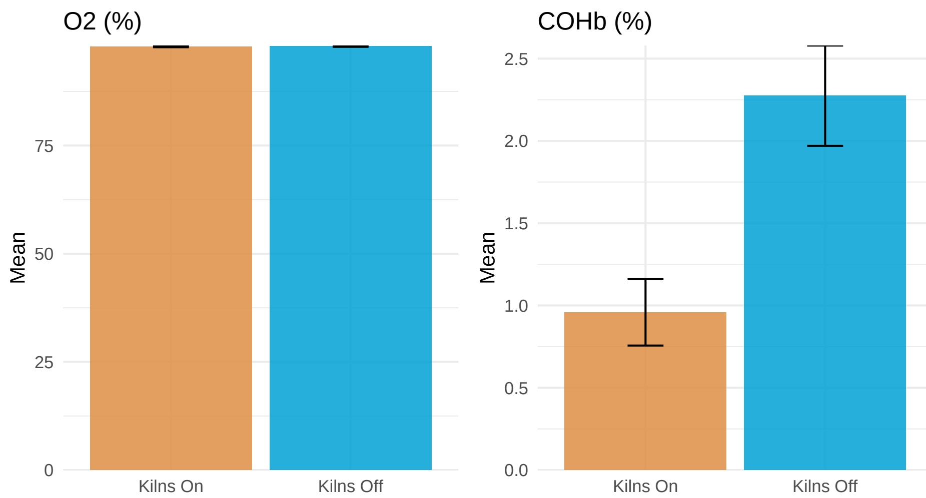


Figure B2: Descriptive plot of other child health outcomes by season. Supplementary Figure B2 presents the average of each of the secondary health outcomes for children under 5 in the brick season (orange) and the off season (blue). The black bars indicate $\pm$ 1.96 standard deviations around the mean.

Table B1: Difference-in-difference results for secondary outcomes

	Downwind from kiln (2 km)		Inverse Sum Score	
	Coefficient (95% CI)	N	Coefficient (95% CI)	N
COPD, by spirometry (Adults 40+)				
Unadjusted	3.84 (0.47, 31.59)	952	1.25 (0.92, 1.7)	2,398
All Controls + Village FE	3.71 (0.38, 36.47)	434	1.27 (0.94, 1.73)	1,378
Hypertension (Adults 18+)				
Unadjusted	0.91 (0.68, 1.23)	1,749	0.97 (0.93, 1.01)	4,408
All Controls + Village FE	0.85 (0.61, 1.18)	1,732	0.97 (0.93, 1)	4,387
Systolic BP (Adults 18+)				
Unadjusted	0.33 (-3.58, 4.24)	1,756	-0.05 (-0.38, 0.28)	4,422
All Controls + Village FE	0.4 (-3.67, 4.47)	1,756	-0.04 (-0.39, 0.3)	4,422
Blood Oxygen Levels (Adults 18+)				
Unadjusted	0.09 (-0.44, 0.62)	1,764	-0.04 (-0.1, 0.01)	4,436
All Controls + Village FE	0.08 (-0.47, 0.64)	1,764	-0.05 (-0.11, 0.02)	4,436
Blood Oxygen Levels (Children $\leq$ 5)				
Unadjusted	0.11 (-0.78, 0.99)	187	0.11 (-0.78, 0.99)	187
All Controls + Village FE	0.07 (-0.87, 1)	187	0.07 (-0.87, 1)	187
Blood CO Levels (Adults 18+)				
Unadjusted	-1.02 (-2.45, 0.42)	671	-0.04 (-0.16, 0.07)	1,570
All Controls + Village FE	-1.08 (-2.52, 0.36)	671	-0.06 (-0.17, 0.05)	1,570
Blood CO Levels (Children $\leq$ 5))				
Unadjusted	-0.25 (-3.88, 3.39)	61	-0.25 (-3.88, 3.39)	61
All Controls + Village FE	-0.76 (-5.82, 4.3)	61	-0.76 (-5.82, 4.3)	61

Notes: This table presents difference-in-difference using both the binary kiln exposure (downwind from a kiln within 2 km), shown in the first two columns, and the inverse sum score, shown in the second two columns for the secondary health outcomes: COPD (measured by spirometry), hypertension (systolic BP $\geq$ 130 mmHg or diastolic BP $\geq$ 80 mmHg), systolic BP, blood oxygen levels, and blood carbon monoxide levels (COHb). Models for COPD and hypertension were estimated using logistic regression and odds ratios are reported, with 95% confidence intervals shown in parentheses. Models for systolic BP, blood oxygen levels, and blood carbon monoxide levels were estimated using linear regression. Controls for health outcomes include sex, age, educational attainment (adults only), a household asset index, an indicator for whether the household owns land, an indicator for whether the household is constructed from quality materials, household size, hours of electricity, a binary variable for whether the household cooks with biomass fuel, a binary variable for smokers present in the home, whether the individual is aware of pollution (adults only), and whether the individual has worked on a brick kiln (adults only), average elevation, population density, distance to the closest road, distance to Mirzapur City, and distance to Dhaka City. Note that due to difficulties collecting blood oxygen and carbon monoxide levels using the standard finger pulse oximeter for children under 5, sample sizes are smaller.

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