Dust Exposure and Infant Mortality in West Africa*

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Abstract

Dust pollution in West Africa increases infant mortality. Employing differences in differences, we make three contributions. First, using data from several poor countries, we highlight the vulnerability of people with few resources, fragile health, and limited capacity to adopt avoidance behavior. Second, we examine prenatal and post-natal parental responses, and show evidence consistent with either compensating parental investments or greater availability of such investments. Despite these efforts, the health of surviving children is adversely affected. Third, we find declining effects over time, implying that societies are adapting. We find suggestive evidence that economic growth has contributed to this adaptation.

Keywords: Dust, Infant Mortality, West Africa, Adaptation

JEL Classification Codes:

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1 Introduction

Research over the past decade has emphasized the adverse effects of weather fluctuations on important outcomes related to economic growth and development, including conflict, mortality, disease, and income (Dell et al., 2012; Hsiang et al., 2013; Maccini and Yang, 2009). The links between weather, health, and the ability of people to adapt are particularly salient in developing countries. First, health is more fragile in these contexts, implying that small changes in weather conditions could have large impacts on health outcomes. Second, coping mechanisms for adjusting to extreme weather events are fewer than in other countries. For example, while migration was a major response to the American Dust Bowl (Hornbeck, 2012), studies in Bangladesh show that individuals persist in not migrating, even in chronically flood-prone areas (Bryan et al., 2014). Third, as developing countries raise their standards of living, it is critical to examine whether economic growth is accompanied by increased adaptation, mitigating the impacts of weather events.[1] Finally, climate change is likely to exacerbate preexisting inequalities in income, health, and human capital. Examining the effects of weather-related events on such outcomes is, then, crucial in the developing country context.

This paper presents one of the first large scale empirical analyses of the impacts of *in utero* dust exposure in Western Africa on mortality in early childhood. Our analysis spans two decades, from 1986 to 2006, allowing us to examine adaptation responses. Our data covers 12 countries, allowing for an exploration of the effects of dust exposure across countries with different public health systems. Our study focuses on a specific source of dust-related pollution in the African Sahel: a yearly trade wind that blows from the Sahara towards the Gulf of Guinea, known locally as the *harmattan*. It carries with it a large amount of dust, mostly quartz, clay, colloids, and fine mica flakes (Besancenot et al., 1997).[2] Recent

[1] This has been shown recently in the United States with regards to the adoption of air-conditioning as a mitigating mechanism against temperature shocks (Barreca et al., 2015).

[2] Abdurrahman and Taqi (1982) give the composition of Saharan dust as silica (50%), alumina (10%), lime (5%), ferric oxide (4%) and other salts (5%).

harmattan activity in Nigeria has sparked enquiry into whether global warming could be partly responsible for changes in the timing and intensity of the dust storms (Gambrell, 2010).

The *harmattan* is known to cause widespread damage to infrastructure, disrupt flights, reduce rainfall, and affect crop outputs (e.g. Adefolalu (1984); Adetunji et al. (1979)). It is correlated with outbreaks of meningitis (Besancenot et al., 1997). In this paper, we are not able to distinguish the relative importance of these mechanisms; rather, our main goal is to show the reduced form relationship between the *harmattan* and infant mortality across multiple countries and over time. Our research is aided by the availability of data on dust concentrations taken from NASA satellite data and extrapolation verified by on-the-ground measurements. Our specific measure of dust is PM2.5, or particulate matter whose size is less than 2.5 microns. Our focus on outcomes in early childhood is motivated by research over the past decade emphasizing this critical period of child development (Cunha and Heckman, 2007). Examining the impacts of environmental shocks such as dust on post-birth health indicators is complicated by the fact that parental investments might react to early childhood health shocks (Adhvaryu and Nyshadham, 2014; Bharadwaj et al., 2013b). Indeed, we examine whether early life parental investments in child health such as breastfeeding, vaccinations and health care usage respond to dust exposure and find that, even in the short run, there appears to be a significant behavioral response. Hence, our results should be interpreted as the effect of dust exposure net of any reinforcing or compensating parental investments or net of any direct *access* effects due to dust exposure.[3]

We find compelling evidence that exposure to dust *in utero* affects early life survival. Additional exposure of 10 $\mu g/m^3$ of PM2.5 during each month of gestation decreases infant survival by 2.3 percentage points, which is substantial relative to the sample average infant mortality rate of 11.2%. However, between 1986 and 2006, the effect of PM2.5 dust on mortality shows a steady decline; the effect more than halves during this time period. This

[3] See Almond and Mazumder (2013) for a discussion of reinforcing or compensating parental investments.

suggests that these impacts have been mitigated by better adaptation tactics, by the spread of public health services, or by better technological advances, among other potential explanations. Using data on per capita GDP at the country level, we find suggestive evidence that the effect is smaller in countries with higher levels of income. We do not, however, find evidence that this is due to greater health expenditure, which is itself either weakly or positively correlated with the strength of the effect of dust exposure on mortality. At the individual level, we find that children born to older mothers are less susceptible to the deleterious effects of dust. This again suggests a socio-economic gradient in the dust-mortality relationship.

Our empirical approach controls for standard concerns faced by studies that examine the role of pollution exposure on mortality. A major concern, for example, is sorting. Individuals might sort into areas with lower dust prevalence and characteristics that are associated with sorting could affect early childhood mortality. Similarly, children born in different months of the year could also be exposed to other seasonal variation or environmental agents, which could drive part of the correlation of dust exposure with mortality. There can also be broad secular trends at the national level with declining infant mortality that might affect our results. To control for these factors, our main empirical specification includes survey cluster fixed effects, where clusters approximate villages and are defined uniquely for every wave of the survey. We include country by month fixed effects that allow for different seasonal patterns by country. Our baseline also includes year of birth fixed effects and country-specific linear time trends. That is, we compare two children from the same survey cluster exposed to varying levels of dust by virtue of being born at different times, over and above any unobserved shocks to mortality that vary by year of birth, the typical country-specific monthly pattern of mortality, and the long-run trends in that child's country. We further add controls for rainfall and temperature during the *in utero* period. In addition, our results are robust to an alternative mother fixed effects approach, in which we compare siblings born at different times and hence exposed to different dust levels, but who otherwise share similar family and location characteristics.

1.1 Contribution

This paper is related to the broader literature examining the impacts of environmental factors on health outcomes. Given that health and mortality shape the economic impacts of the *harmattan*, the results of this paper can be related to work examining the health impacts of exposure to weather related changes in income in developing countries as in Maccini and Yang (2009), Adhvaryu et al. (2014), Baird et al. (2011), Burgess et al. (2014), and others. More directly, fine dust inhalation can directly affect health of the fetus and result in lower health at birth, increasing the risk of neonatal and infant mortality. In particular, given that we examine these impacts across countries in Western Africa, our paper relates to some of the emerging literature examining the health impacts of pollution exposure in developing countries (Arceo-Gomez et al., 2015; Ebenstein, 2012; Greenstone and Hanna, 2014). Our paper also contributes to this literature by examining these impacts across a diverse set of countries and over two decades. Baseline vulnerability may differ over time and across levels of economic development, as may the costs of avoidance and recovery behaviors.

Although we are not the first paper to investigate the link between natural air pollution and mortality in a poor country (e.g. Jayachandran (2009)), the existing literature remains small. Our data allow us to expand the evidence on the external validity of existing findings. Similarly, our focus on a naturally occurring source of pollution allows our results to be uncontaminated by other policies that might coincide with environmental regulations and similar sources of identifying variation used in many standard differences-in-differences frameworks. In this sense, our contribution resembles that of Jia and Ku (2015), in a developing country context and over a broader spatial and temporal scope. Because we focus narrowly on mortality, parental investments, and health outcomes before age five, ours is not a complete accounting of the negative effects of fetal dust exposure; ours is only an assessment of one portion of the overall cost.

Another advantage of considering such a broad region over a long time period, using data that record multiple parental investments, is that we are able to test the degree to which people and institutions are adapting to the adverse effects of dust exposure. In this regard, our paper builds on the evidence presented in Barreca et al. (2015) in the context of several developing nations and over a critical period of their growth. This is a literature in which there is a clear need for more empirical research. Even in the case of the health effects of environmental shocks for which there is a large literature (temperature) and in contexts where avoidance behaviors can be reliably measured (rich countries), existing knowledge on adaptation is quite limited (Deschenes, 2014). Many pioneering studies that evaluate the effects of pollution on mortality in developing countries are able to compare the effects to those in rich countries and to identify a socio-economic gradient, but cannot track adaptation over time or measure avoidance behavior. In other cases, diminishing mortality has not been due to better mitigation, but rather to improved air quality (Arceo-Gomez et al., 2015). As Arceo-Gomez et al. (2015) note, the effects of pollution may be more severe at the higher levels found in poor countries, and the costs of avoidance behavior may be greater. This is true of many types of environmental shocks to health (Burgess et al., 2014; Dell et al., 2014; Kudamatsu et al., 2012). As a result, we may not expect diminishing effects of shocks over time like those found in the developed world.[4] We do, however, find evidence that the effects of fetal dust exposure on the survival of West African children has lessened in recent years.

2 Empirical strategy

To test for the effects of dust exposure during the *in utero* phase on neonatal, infant, and child mortality, we use ordinary least squares (OLS) to estimate the following equation:

[4]Adhvaryu et al. (2015), for example, find no evidence that the effect of *in utero* temperature exposure on adult mental health in Africa has improved over time.

$$Mortality_{icvym} = \beta Dust_{cvym} + x'_{icvym}\gamma + \delta_{cm} + \eta_y + \theta_{cv} + \phi_c \times y + \epsilon_{icvym}. \qquad (1)$$

Here, $Mortality_{icvtm}$ is an indicator for child i, born in month m in year t, whose mother is surveyed in cluster v in country c. v can loosely be thought to index "villages." Neonatal mortality is death within the first month of life. Infant mortality is within the first twelve months, and child mortality is within the first 60 months. $Dust_{cvym}$ is the level of dust pollution recorded at the dust point closest to v in the 9 months preceding month m in year y. Thus, we assume a gestation period of 9 months for all births – this is unfortunately not a testable assumption in our data. We use a cumulative exposure measure, summing the dust reading for each month during gestation. β is the coefficient of interest, and we expect it to be positive. x_{icvym} is a vector of controls. In our preferred specification, it includes average rainfall 9 months prior to birth, average temperature 9 months prior to birth, the squares of these terms, the interaction between average rainfall and temperature, child birth order, child female, child is a multiple birth, mother's age at birth, mother's age at birth squared, mother's years of education, and mother's religion. We also include three additional and important sets of fixed effects, First, country $\times$ month of birth fixed effects (δ_{cm}) account for general seasonal variation in birth outcomes that may vary across countries. Second, year-of-birth fixed effects (η_y) account for time specific shocks such as economic crises and disease outbreaks. Finally, θ_{cv} captures cluster fixed effects that will absorb any unobserved drivers of mortality that happen to correlate with dust over space. We also include country time trends $\phi_c \times y$ to account for other possible unobserved trending variables that may vary by country.

Hence, the variation in PM2.5 used in this paper is variation across children from the same survey cluster whose exposure to dust *in utero* was determined by differential birth timing, but cannot be explained away as the effect of other country-specific patterns of seasonality, country-specific time trends, annual shocks that affect the whole of West Africa, or very flexible functions of rainfall and temperature. We cluster standard errors by dust point; as a robustness exercise we will show that clustering by administrative regions has little effect on the results.

We estimate several alternative versions of the above model. For example, while examining how the effect of dust on mortality has changed over time, we include the interaction of time trends with the dust variables. In these models, the standard assumption is that, after controlling for seasonality, temperature, rainfall and country specific time trends, *in utero* dust is uncorrelated with the error term. We interpret this as the *overall* effect of dust on mortality, or the *unmediated* effect of dust on mortality. It is certainly likely that dust exposure can affect incomes, parental investments and other behavioral responses. To examine the extent of these mediating factors, we also estimate a version of equation (1) in which we replace the dependent variable with measures of this mediating behavior. Hence, our main interpretation of the effect of dust on mortality is *net* of these behavioral responses to dust exposure, i.e. it is the reduced form effect.

3 Data

In this section, we describe the data sources used in the analysis. Additionally, where necessary, we describe the construction of the variables of interest.

3.1 Dust

We take data on dust from the International Research Institute for Climate and Society at Columbia University.[5] These data are available for the period from August 1985 to December 2006 at latitude-longitude intervals of 1.25° by 1.25°. These will allow us to compute fetal dust exposure for children born between April 1986 and December 2006.

[5] The data can be downloaded from `http://iridl.ldeo.columbia.edu/home/.nasa_roses_a19/.Dust_model/.dust_mon_avg/.dust_pm25_sconc10_mon/`

Constructed using NASA satellite measurements, the dust data report hourly concentrations of $PM_{2.5}$, or particulate matter smaller than than 2.5 micrometers. We convert these data to monthly format in order to merge them with the Demographic and Health Survey (DHS) datasets described below. Particulate concentrations are reported in hundreds of micrograms per cubic meter.

These data are the result of the NMMB/BSC Dust model, which was developed at the Barcelona Supercomputing Center in collaboration with the NASA Goddard Institute for Space Studies and the National Centers for Environmental Protection (Pérez et al., 2011). This model simulates soil dust aerosol emission, which has been validated using existing satellite and in situ data over this region (García-Pando et al., 2014; Pérez et al., 2011). The correlation between the soil dust aerosol component of this model and aerosol optical depth (AOD) is around 0.6 (Ceccato et al., 2014; Pérez et al., 2011). Additional information on these data is presented in Stanley (2013). This dust model also predicts PM10 pollution; hence, while we primarily use PM2.5 as our main dust exposure variable, we also show our main results using PM10 as the dust variable.

3.2 Demographic and health survey data

Our principal outcomes of interest are taken from 128 DHS datasets from West Africa. These have been collected from several West African countries since the mid-1980s. We use all standard West African DHS surveys for which geographic coordinates are available; these coordinates are needed for merging with the data on dust. Our sample, then, includes Benin, Burkina Faso, Ghana, Guinea, the Ivory Coast, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, and Togo.

The data come in four formats:

1. The *Individual Recodes* survey women who are aged between 15 and 49. These nationally representative cross-sections contain several variables that we use. These include

the woman's year of birth, her level of education, whether she lives in a rural area, her age, her occupation, the occupation of her partner, and her self-reported religion.

2. The *Births Recodes* are complete birth histories of the women surveyed in the individual recodes. We use these data for our main results. In particular, we make use of the child's year and month of birth, birth order, an indicator for a multiple birth, a dummy for female, and the length of the child's life.

3. The *Children's Recodes* are similar to the births recodes, but contain a larger amount of information about a smaller number of children. Women are asked about births in the previous five years. In addition to controls available in the births recodes, these include early life investments such as vaccinations and breastfeeding. Additional prenatal investments are also recorded, including care from doctors and the circumstances of the child's birth.

4. The *Geographic Datasets* record latitude and longitude coordinates for the survey clusters in the data. We use these coordinates to merge children to the nearest point in the dust data, assigning each child the level of dust of the nearest point. These are shown in Figure 1.

3.3 Matching DHS to dust data

Figure 1 shows how DHS clusters are matched to their closest dust grid points. Colored dots are DHS clusters (the variation in colors represents how much average dust exposure these clusters have), while the dark squares are the dust points on the grid.

3.4 Summary statistics

Table 1 shows the summary statistics used in this paper. Infant mortality over the births in our data during the 1986-2006 period for all the countries considered averages 11.2%. Child mortality is relatively high in this region, even by the standard of developing countries.

However, as Figure 2 suggests, most countries in our data set have experienced substantial declines in infant mortality over this period. Figure 2 also suggests substantial heterogeneity in infant mortality across West African nations: some of lowest rates are seen in Ghana and Senegal (averages of 7.7% and 8.1% respectively), while the highest averages are seen in Mali and Niger (13.8% and 13.3% respectively).

The average PM2.5 concentration is around $44\mu g/m^3$ over the entire sample.[6] To put this in perspective, the average annual PM2.5 concentration in Southern California was 20 in 1999 (EPA), while the recent estimates from New Delhi put its annual PM2.5 concentration at 153 (WHO 2014). However, this average measure hides substantial within-year variation in PM 2.5. As Figure 3 suggests, there are stark seasonal patterns in PM2.5, with the highs typically observed January through April. Despite anecdotal evidence that the *harmattan* is becoming more severe over time or that it now reaches parts of West Africa that were unaffected within living memory (e.g. Abdurrahman and Taqi (1982)), Figure 3 shows that for the sample period (1986-2006) there appears to be no obvious yearly trend in PM2.5 levels.

Table 1 also shows some of the key characteristics of mothers in our sample. Mothers overall have low levels of education (an average of 1.6 years), and are young. The average age at the child's birth is nearly 26 years, but note that the average birth order observed in the data is 3, suggesting women typically have 3 children by age 26 in the sample. Controlling for these characteristics can be important since attributes such as maternal education and age can have a direct bearing on a child's health.

4 Results

Table 2 shows the effects of *in utero* dust exposure on neonatal (within 28 days of birth), infant (within a year of birth), and child (within 5 years of birth) mortality. Including controls such as maternal characteristics, rainfall, and temperature increases the effect size

[6] That is, 4.11 $\times$ 100 (Table 1 reports 100s of $\mu g/m^3$) $\times \frac{1}{9}$ (i.e. per month *in utero*).

in all specifications, suggesting that it is unlikely that omitted variables correlated with dust exposure are driving our results (Altonji et al., 2005).[7]

While it is interesting to present results for all three kinds of mortality, we focus on the results on infant mortality as the interpretation of the other coefficients are similar. There is little evidence of greater mortality in the first month, but there are substantial effects on both infant and child death. Column 4 of Table 2 shows that the effect of a one standard deviation increase in *in utero* PM2.5 leads to a 0.39 percentage point increase in infant mortality, or roughly 3.5% of the mean.[8]

Three other thought experiments help make the magnitude of these results interpretable. First, consider reducing exposure to PM2.5 by 10 units in every month of gestation, or $90\mu g/m^3$ over an entire pregnancy. This would reduce infant mortality by 0.23 percentage points, or roughly 2.1% of the mean.[9] Second, consider reducing exposure to levels deemed acceptable by the EPA's PM2.5 national standards in the US ($15\mu g/m^3$). This would reduce mean exposure from 411 $\mu g/m^3$ over an entire pregnancy to 135 $\mu g/m^3$, reducing infant mortality by 0.71 percentage points, or 6.4% of the mean.[10] Third, contrast children born in December with those born in July in the dustiest 20% of clusters in the data, i.e. in the parts of West Africa where seasonal dust is most salient. The former experiences a mean cumulative dust exposure of 430 $\mu g/m^3$, while the latter has a mean exposure of 668. Relative dust exposure raises the relative survival rate of children in the more favorable birth month by 0.61 percentage points.[11] These are the months corresponding to least and

[7] In additional results (not reported), we control for the number of battle deaths during the *in utero* period within 100km of the child's survey cluster as reported by the UCDP Georeferenced Event Dataset (UCDP GED) version 2.0. This has little effect on the results. Battle deaths data only begin in 1989, which reduces the sample.

[8] To see this, multiply the standard deviation of cumulative dust exposure from Table 1 (1.52) by the coefficient (2.581) and divide by 10 to convert from deaths per 1,000 to percentage points.

[9] To see this, multiply the additional dust exposure (90) by $\frac{1}{100}$, since dust is measured in 100s of $\mu g/m^3$ in the regression. Multiply this by the coefficient 2.581 and divide by 10 to convert from deaths per 1,000 to percentage points.

[10] To see this, multiply the reduced dust exposure (276) by $\frac{1}{100}$, since dust is measured in 100s of $\mu g/m^3$ in the regression. Multiply this by the coefficient 2.581 and divide by 10 to convert from deaths per 1,000 to percentage points.

[11] To see this, multiply the reduced dust exposure (239) by $\frac{1}{100}$, since dust is measured in 100s of $\mu g/m^3$ in the regression. Multiply this by the coefficient 2.581 and divide by 10 to convert from deaths per 1,000

greatest mean exposure in these clusters.

We can put these results in the context of other interventions or environmental shocks considered in the literature. Our results are smaller than some other shocks considered in the literature, but still comparable. These include the 3.27 percent decline in American infant mortality due to reductions in the use of bituminous coal for heating (Barreca et al., 2015), the 3.5 percentage point increase in mortality due to a six-month malaria epidemic (Kudamatsu et al., 2012), the 1.8 percentage point effect of democratization in Africa (Kudamatsu, 2012), the elasticity of rural infant mortality with respect to aggregate income of -0.33 in India (Bhalotra, 2010), or the 7.3% annual mortality increase due to a one standard deviation increase in high temperature days in India (Burgess et al., 2014).

By contrast, the effect we find of a one standard deviation increase in dust exposure is similar to the 1.2 percent effect on cohort size of wildfires in Indonesia (Jayachandran, 2009). While Arceo-Gomez et al. (2015) find that a 100 $\mu g/m^3$ increase in PM10 in Mexico city increases deaths by 0.23 per 1000, our results suggest that the same increase in PM2.5 would increase fetal death by 2.581 per 1000. In Appendix Table A1, we replace PM2.5 measures with PM10. We find a corresponding effect of 0.626 that compares directly to their estimate of 0.23.[12] Our effect is also larger than the 0.24 to 0.40 deaths per thousand brought on by a 1% decline in GDP in poor countries (Baird et al., 2011) or the insignificant effect of air regulation in India (Greenstone and Hanna, 2014).

4.1 Robustness checks

In Table 3, we consider alternative sets of fixed effects. Our aim is to show that restricting identification to narrowly-defined comparison groups continues to yield our main results, even if we change the definition of the group used. In column 1, we include fixed effects for country $\times$ month of birth, year of birth, DHS cluster (defined uniquely by survey year), and

to percentage points.

[12]More precisely, they report that a 1 $\mu g/m^3$ increase in PM10 in Mexico city increases deaths by 0.23 per 100,000.

country time trends. In column 2, we include fixed effects for country $\times$ month of birth, year of birth, year of survey $\times$ country, dust point, and country time trends. That is, it is the same as the baseline reported in Table 2. In column 3, we include fixed effects for country $\times$ month of birth, country $\times$ year of birth, and DHS cluster (defined uniquely by survey year).

Column 4 adds country time trends, as well as fixed effects for country $\times$ month of birth, year of birth $\times$ month of birth, and DHS cluster. Column 5 instead includes fixed effects for year of birth $\times$ month of birth, country $\times$ year of birth, country $\times$ month of birth, and DHS cluster. In both cases, the results are positive and significant, and are indeed markedly larger than in our baseline.

Column 6 adds fixed effects for year of birth $\times$ month of birth $\times$ country of birth, as well as DHS cluster. Results here are positive though insignificant, and in the case of child mortality, much larger than in the baseline.

Finally, in column 7, we restrict comparisons to siblings by including fixed effects for mothers, alongside fixed effects for country $\times$ year of birth and country $\times$ month of birth. In all cases but column 3 (allowing for very flexible country time trends) we continue to find significant results similar in magnitude to our baseline. Even with highly flexible country time trends we find an effect on child mortality that is only marginally insignificant ($t = 1.48$).

In Table 4, we show that *in utero* dust exposure is not simply a proxy for dust experienced after birth. When using infant mortality as an outcome, we control for dust in the first year of life (column 1). When using child mortality as an outcome, we control for dust in the first five years of life (column 2). In both cases, the main effect of dust *in utero* remains significant. Indeed, estimates are now noticeably larger than in Table 2, again suggesting that unobservable variables correlated with fluctuations in dust exposure are unlikely to be driving our results. The effect of dust during the first year of life on infant mortality is positive, but statistically insignificant. Controlling for PM2.5 during the first 60 months of life does not diminish the effect of *in utero* dust, but does have its own independent effect on the probability that a child dies.[13]

As discussed below, we report several tests for heterogeneous responses in Table 5. In addition, we use that table to address the possibility of selective migration. We restrict our sample to children whose mothers report having lived in their current place of residence their whole lives. Though the effect on infant mortality becomes marginally insignificant ($t = 1.62$), it is nearly identical to the baseline estimate. The effect on child mortality remains significant and is again very close to the baseline estimate. This suggests, first, that selective out-migration or measurement error based on using current GIS data from the DHS do not bias our results. Second, it is evidence that the effect of dust exposure for those incapable of migration as an avoidance behavior is not different from that of the whole sample.

We perform several additional tests for robustness in the Appendix. The sign and significance of our results are largely replicable when we replace PM2.5 measures with PM10 measures in Appendix Table A1. Appendix Table A1 is organized the same way as Table 2 and shows that PM10 exposure *in utero* leads to greater infant and child mortality. The magnitudes are smaller. This is to be expected, as PM2.5 is known to cause greater harm (Schwartz and Neas, 2000).[14]

In Appendix Table A2 we show that alternative measures of *in utero* dust provide similar results, or do not explain away our preferred measure of (accumulated) exposure. It is possible, for example, that it is the intensity of exposure rather than its mean that matters (e.g. (Hansman et al., 2015)). The number of months during which dust exposure was greater than the cluster mean correlates positively though insignificantly with infant and child mortality. High dust exposure measured instead as the number of months in which dust exposure was at least one standard deviation above the cluster average predicts a statistically significant increase in both infant and child mortality. Similar results obtain if the dust level

[13]We have tested whether in utero dust exacerbates the effects of dust after birth. The interaction is positive but insignificant (not reported).

[14]The strong correlation between PM2.5 and PM10 dust prevents us from disentangling their relative effects in the same empirical specification.

during the month of greatest exposure during pregnancy or the log of accumulated dust are used. Controlling for dust variability (the standard deviation of monthly dust exposure *in utero*) does not render our main result on accumulated dust insignificant; nor does controlling for the dust level during the month of greatest exposure.

Similarly, in Appendix Table A5, we account for the fact that the spatial resolution of the dust data is more coarse than that in the DHS in two ways. First, we weight observations by the inverse of the distance to the nearest dust point. Second, rather than joining each DHS cluster to the nearest point in the dust data, we use bilinear interpolation to assign it a weighted average of the dust recorded at the four dust points that surround it. Both exercises give results very similar to our baseline.

Appendix Table A3 shows the sensitivity of the results to excluding survey clusters in which dust exposure is greatest or lowest. Throughout, our results remain stable. The effect is larger in the clusters where mean dust exposure is greater, consistent with the possibility that mothers exposed to greater dust over their lifetimes are more vulnerable to exposure *in utero*, or with the possibility that *in utero* dust exposure makes children more vulnerable to later dust exposure in childhood.

We use Table A4 to show that our results are not dependent on a linear specification. Using deciles of dust exposure shows that, relative to the omitted, lowest-exposure decile, higher treatments of *in utero* dust raise mortality, particularly in the three greatest deciles.

In Appendix Table A6, we show that our results are robust to clustering by administrative region as recorded in the DHS, rather than the nearest point in the dust data. These regions are typically second-level administrative units such as provinces and states. Indeed, standard errors are largely indistinguishable using this approach.

4.2 Mechanisms

4.2.1 Dust exposure and mortality

Broadly, the mechanisms connecting fetal dust exposure to infant and child mortality can be classified as *biological* or *economic*. Biological mechanisms can themselves can be divided roughly into indirect effects operating through the health of the mother, direct effects while in the womb, and greater vulnerability to later health insults. Pregnant mothers who inhale dust are at risk of having particulate matter enter their lungs, which can affect the operation of several organ systems (DeFranco et al., 2015). Dust inhaled during the *harmattan* in particular can carry harmful elemental and biological particles, including heavy metals and trace metals, and can lodge deep in the lungs (Uduma and Jimoh, 2013). Pathways for direct effects *in utero* include interrupted placental development, fetal growth restriction, susceptibility to pre-term birth, heart defects, and reduced weight gain. Ritz and Wilhelm (2008) suggest several effects of air pollution both at birth and that persist afterwards, making children more vulnerable. These include higher risks of: infant death; brain, respiratory, and digestive problems in early life, and; heart disease and diabetes in adulthood. It has also been noted in the literature that the *harmattan* is correlated with outbreaks of meningitis (Besancenot et al., 1997). While the mechanisms remain unclear, the seasonal dust dries the lips and irritates the nasopharyngeal mucosa.

West African populations are generally aware of seasonal correlations between health outcomes and the *harmattan*. Eighteenth-century European observers on the Ghanaian coast observed that fine dust would settle on the skin, giving it a whitish color. Dryness that accompanied the dust harmed vegetables, trees, facilitated the spread of fires, damaged furniture, and irritated the eyes, nostrils, palate, and lips, though the *harmattan* also coincided with declines in infections and epidemics such as smallpox (Dobson and Fothergill, 1781). Several studies have suggested that seasonal dust and dryness might aggravate asthma, carry disease vectors, dry the skin, irritate the throat and eyes, produce catarrh, lead to coughing and bronchitis, and even give rise to sinusitis, pneumonia and respiratory infections (Abdurrahman and Taqi, 1982; Adefolalu, 1984; Quagraine and Boschi, 2008). Websites and newspapers in West Africa note the existence of these seasonal health issues, as well as other problems such as the greater prevalence of fires, and provide tips on keeping one's skin hydrated.[15] Experts, medical staff, and other popular sources of advice suggest individuals take preventive measures such as wearing thick clothing, staying inside, keeping their food covered, washing their hands more regularly, tending fires more carefully, and washing their faces more often.[16] Whether this popular knowledge translates into preventive action is less clear; for many, the *harmattan* is simply thought of as a nuisance (Adefolalu, 1984), though the seasonal cold may make business start later in the morning.[17] Libraries in Nigeria cope with the dust by closing windows, dusting library materials, and attacking the insects blown in with the dust (Ezennia, 1989).

Economic mechanisms are those that change affect the prices, returns, or budget constraints by West Africans. Dust storms may reduce incomes generally by damaging infrastructure, disrupting flights, reducing rainfall, increasing the frequency of fires, and affecting crop outputs (e.g. Adetunji et al. (1979); Jenik and Hall (1966)), though there is some evidence that the *harmattan* aids soil fertility at the fringes of the Sahara (Adefolalu, 1984). Some of the most well known airplane crashes in Nigerian history have occurred during the *harmattan* (Abdurrahman and Taqi, 1982). Reduced parental health may impact labor productivity, and hence income. If infant health is initially harmed by fetal dust exposure, it may reduce the returns to complementary parental investments or, conversely, increase the urgency of interventions that might ameliorate these effects (Cunha et al., 2010). Alternatively, dust storms may either increase the costs of accessing health services, or may prompt a public health response that makes these services more available.

[15] http://www.thisdaylive.com/articles/tips-to-keeping-your-skin-hydrated-during-the-harmattan/106015/, http://allafrica.com/stories/201311180452.html, http://www.thisdaylive.com/articles/asthma-and-the-harmattan/128687/.

[16] http://www.aitonline.tv/post-harmattan_haze__avoiding_the_dry_season_blues, http://howtotellagreatstory.com/2012/11/the-story-of-harmattan-part-1-it-chillsdriesalters-lifestyle/.

[17] http://allafrica.com/stories/201311180452.html

4.2.2 Heterogeneous response

While it is beyond the scope of this study to disentangle all possible mechanisms, we can use heterogeneous response to treatment and the responses of additional outcomes to help reduce the set of plausible explanations and to understand the responses and socio-economic variables that may mitigate the effects of dust. As an empirical approach to uncovering the mechanisms underpinning our results, Table 5 explores their heterogeneity. We interact *in utero* dust exposure with predetermined characteristics of the mother and child. The impact of dust is greater for girls, which is surprising, given that medical research suggests that male fetuses are more fragile than female (Gualtieri and Hicks, 1985; Kraemer, 2000). This is unlikely to be due to selective neglect. We show evidence below of compensating investments that offset the effects of dust exposure. We have also tested whether these offsetting investments are less for girls (not reported), but instead find that these investments are indeed greater for girls. If only relatively healthy boys survived to birth, this could explain their relatively better post-birth outcomes (see Dagnelie et al. (2014) for an example). However, we find no evidence of this; we show below in Appendix Table A7 that there is no evidence that boys are less likely to survive from conception to birth. Together, these results suggest a biological mechanism in which female fetuses are indeed more directly affected by dust exposure. Parents recognize this and increase their compensating investments, but cannot fully offset the effects.

Some, though not all, socio-demographic characteristics are protective in nature. For example, the impact of PM2.5 exposure is smaller for older mothers. Though we find no heterogeneity by wealth in infant mortality, the effect of dust on child mortality is significantly reduced for children whose households are wealthier, according to the DHS's wealth index.[18] Similarly, the effect on child mortality is larger for those with poorer quality housing,

[18]This index is made available in the DHS data and is not constructed by the authors. It aggregates the assets owned by the household using factor analysis. A greater score on the index indicates ownership of more items such as radios or motorcycles. We lose sample size in this specification because it is missing for a large number of observations.

as proxied by a mud floor. Though it is insignificant, the interaction with mother's education is negative. If we interact dust exposure with whether the child's mother reports working at home, the interaction is negative, but not significant. So: we have only weakly suggestive evidence that women who typically stay indoors inhale less dust during pregnancy. We find no significantly greater effect for those living rural areas, though the coefficient is positive. If dust has greater adverse effects on rural incomes than urban incomes, for example through erosion and crop damage, this suggests direct inhalation is a more important mechanism than the possible economic channels. Similarly, since most cooking in urban areas is indoors, this rules out a perverse mechanism by which dust pollution encourages greater indoor cooking and, as a result, exposure to smoke and other indoor pollutants.

In the Appendix, we further explore heterogeneous response to dust exposure. In Appendix Table A8, we disaggregate dust exposure by trimester. The magnitude and significance of dust exposure in the first trimester is greater than exposure for the second and third trimesters. This is consistent with other studies that have found larger effects on mortality, birth weight, and later-life outcomes for insults occurring early in pregnancy (Almond and Mazumder, 2011; Camacho, 2008). This also suggests that nutrition is not the sole source of the effects we find, as fetal health is particularly sensitive to nutrition in the final trimester (Almond et al., 2011).

4.2.3 Selective fertility and survival to birth

Two forms of sample selection might explain some portion of our results: selective survival of only some fetuses to term, and selection of the types of parents whose fertility coincides with variations in dust exposure. The DHS do not collect information on miscarriages in a way that would permit us to directly measure whether death *in utero* responds to dust exposure. The fact that our estimated effects are similar when conditioning on mother fixed effects above suggests that selection by parental characteristics is unlikely to explain our results.

Further, we perform analyses similar to those in Buckles and Hungerman (2013), demonstrating that neither parental characteristics nor child characteristics correlate with dust. These include child gender, child birth order, whether the child is a twin or other multiple birth, the mother's age, and the mother's years of schooling. In particular, we report estimates of (1) with these variables as outcomes in Appendix Table A7, though without controlling for individual or maternal characteristics. With one exception, we find no evidence that dust exposure predicts pre-determined characteristics, making selective fertility an unlikely explanation of our results. The lone exception is a positive correlation between dust exposure and maternal education. The most plausible explanation of this correlation is that children of more educated mothers were more likely to survive from conception to birth, which would bias our baseline results towards zero.

Finally, in Figure 4, we provide additional evidence that selective fertility does not explain our results. First, we plot the relative frequency of births in each month, separately for clusters defined by quintiles of mean dust. Second, we plot the average education of mothers for the births recorded in each month. This too is by quintile of mean dust exposure. In the first figure, it is clear that there is a seasonal pattern to fertility in the data, but it is not one that differs across regions heavily affected by dust pollution and those that are not. In the second case, there is little evidence of seasonal variations in the characteristics of mothers that might correlate with seasonal dust.

4.3 Behavioral responses and other outcomes

Having established a reduced form effect of PM2.5 on infant mortality and its robustness, we next document whether this effect is mediated by behavioral responses by parents. Table 6 examines whether dust exposure *in utero* affects subsequent investments by parents. We find that greater dust exposure leads to greater health investments by parents. Such behavior can arise from two primary sources that we are unable to disentangle in these data. First, this could be the result of greater access to health care after a high dust period. If high dust periods are followed by government or NGO intervention to increase the availability of services such as health centers, this could explain part of the effect. A second explanation could arise from the idea that parents invest more in weaker children in the post natal period. This "compensatory" or mitigating behavior contrasts with the "reinforcing" behavior of parents found in some developing country settings where parents have limited resources and choose to invest only in children with the highest "potential" (Almond and Mazumder, 2013; Bharadwaj et al., 2013a).[19]

Table 6 examines these behavioral responses further and provides more direct evidence about the relative importance of "access," relative to post-birth parental responses. Table 6 examines *pre natal* investments and finds that greater dust exposure has little effect on choices such as antenatal visits for pregnancy and delivery in a hospital. Since these investments are made before the child is born, this would capture the effect of dust events on access to health centers that provide vaccinations and on access to doctors who can attend to the delivery. Rather, it is investments (vaccinations) made after birth that respond in Table 6. This is suggestive of parents undertaking compensatory investments once child quality is revealed, rather than facing greater access to investments or anticipating health effects to which they will later need to respond.

Despite compensating investments after birth, it is likely that these will not be completely effective, and dust exposure will result in lower health even if the child survives. This is explored in Table 6, where we examine the role of *in utero* dust exposure on various measures of early childhood health. Many of these measures, notably weight for height, weight for age, and height for age represent measures of nutrition and respond negatively. Birthweight responds negatively, but this is marginally insignificant ($t = 1.57$).

[19]Our results are suggestive of compensatory investment, but our data do not allow us to evaluate whether parents respond specifically to the shock that affects the child (in this case, dust exposure) or to revealed child health after birth (such as low birth weight or bouts of illness).

4.4 Effects over time and across countries

Having established the basic result that dust exposure is harmful to children and that direct biological impacts are only partially offset by parental responses, we next exploit the fact that our data spans 20 years between 1986-2006 to see how the impact of dust on mortality has changed over time.

Figure 5 shows the estimates of estimating the effects of dust on infant mortality separately for each year in our sample. Because this prevents us from including base controls such as year fixed effects or trends, we estimate a more parsimonious specification:

$$Mortality_{icvym} = \beta_y Dust_{cvym} + x'_{icvym}\gamma + \delta_{cm} + \phi_{ct} + \epsilon_{icvym}. \tag{2}$$

Hence, each point on Figure 5 is a regression coefficient of the effect of *in utero* exposure on infant mortality for a given year, or β_y. For each estimate, the sample includes only children born in that year. ϕ_{ct} is a fixed effect for the DHS survey conducted in year t in country c; in our baseline regression this is absorbed by the fixed effects for survey clusters. Other variables and parameters are as in our baseline.

Figure 5 shows a clear pattern of a decline in the impact of dust on mortality. The impact of dust appears to decrease by more than half over this time period. Table 7 confirms these effects by showing an interaction of dust exposure with a linear time trend - the interaction is negative, statistically significant, and shows a rapidly diminishing effect. This finding suggests adaptation or other health supply side responses or health technology improvements over time that have helped mitigate these negative impacts.

A more direct test of this is in Table 8, in which we interact dust with country level macroeconomic variables. The sample is smaller here, since we observe country level variables only from 1995 to 2006. The first panel of Table 8 suggests that in general, the effects of dust are smaller in richer countries. However, the lower panel is inconsistent with the view that greater GNI reduces mortality by allowing countries to spend more on health care.

Conditional on controlling for income, the bottom panel shows that the interaction of per capita health care spending and dust exposure is insignificant in the case of both infant and child mortality.

5 Conclusion

This paper shows that PM2.5 dust in West Africa has an economically meaningful and statistically significant impact on infant mortality during the years 1986-2006. While many papers have studied the impacts of *in utero* pollution exposure on early life health, our paper makes additional contributions to this literature.

First, by examining these effects in the context of developing countries, we highlight the greater vulnerability of people with fewer resources to adopt avoidance behavior against dust. Second, we examine parental responses, both in the prenatal and in the post natal stages to show that dust pollution in this context can be mitigated in part by investments shaped by compensating parental behaviors or direct access to health centers and doctors. Third, we examine the effects of dust over time and find a steady decline in its impacts. This suggests that, over time, people and countries are adapting to the harmful effects of dust. Using country income, we show that West African countries with greater overall levels of development experience lower mortality impacts due to dust.

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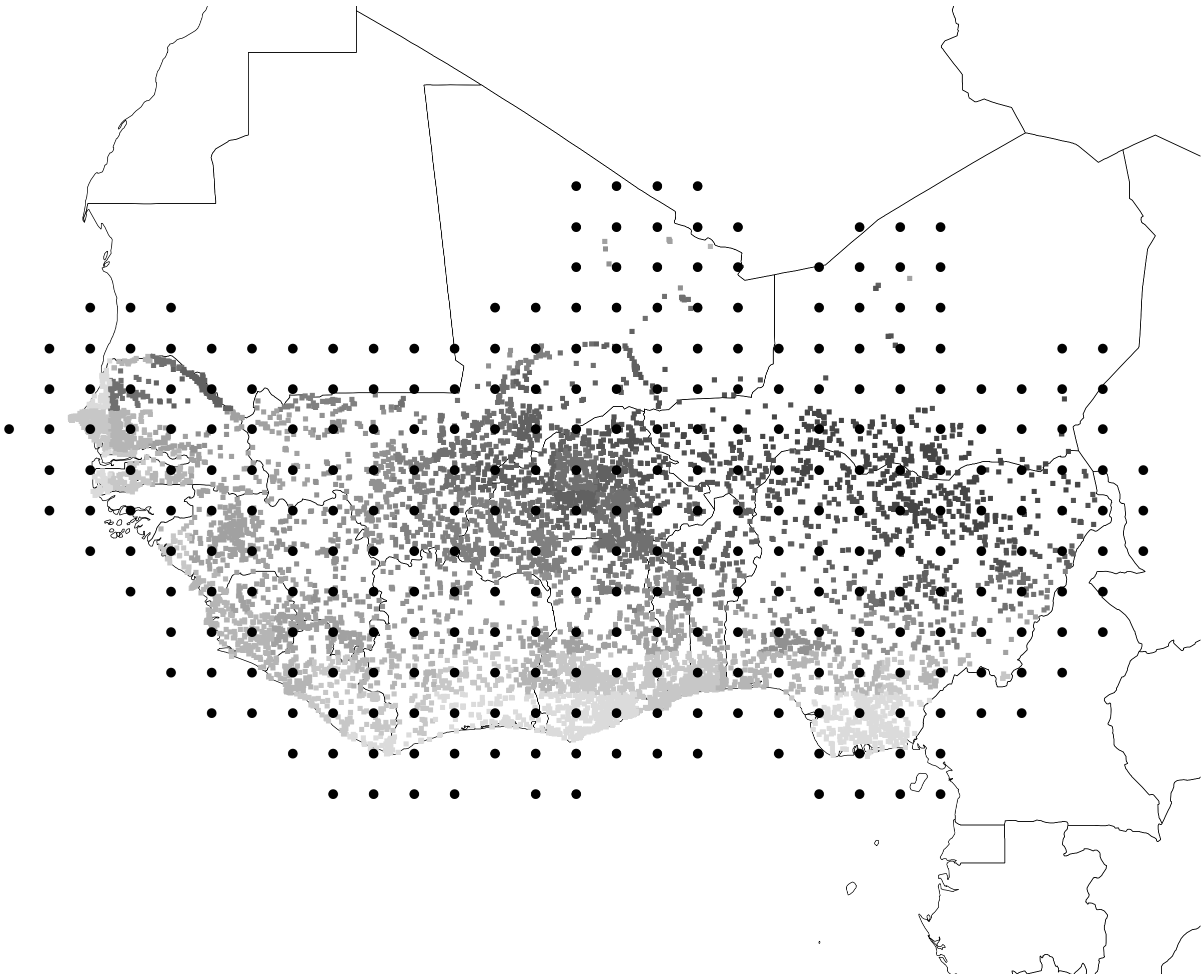
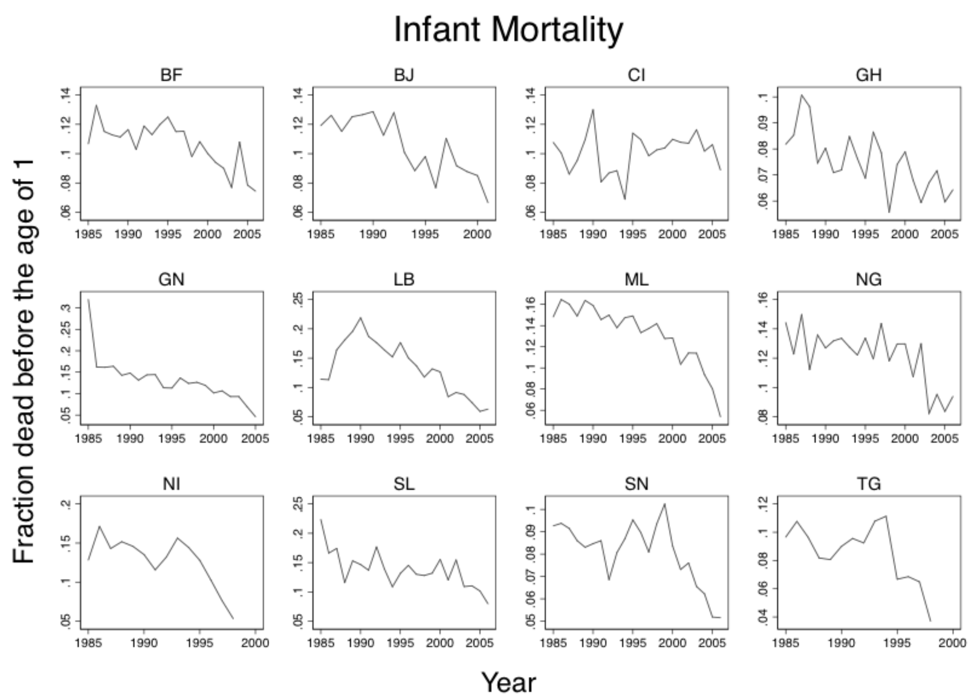
Figure 1: DHS clusters and dust points



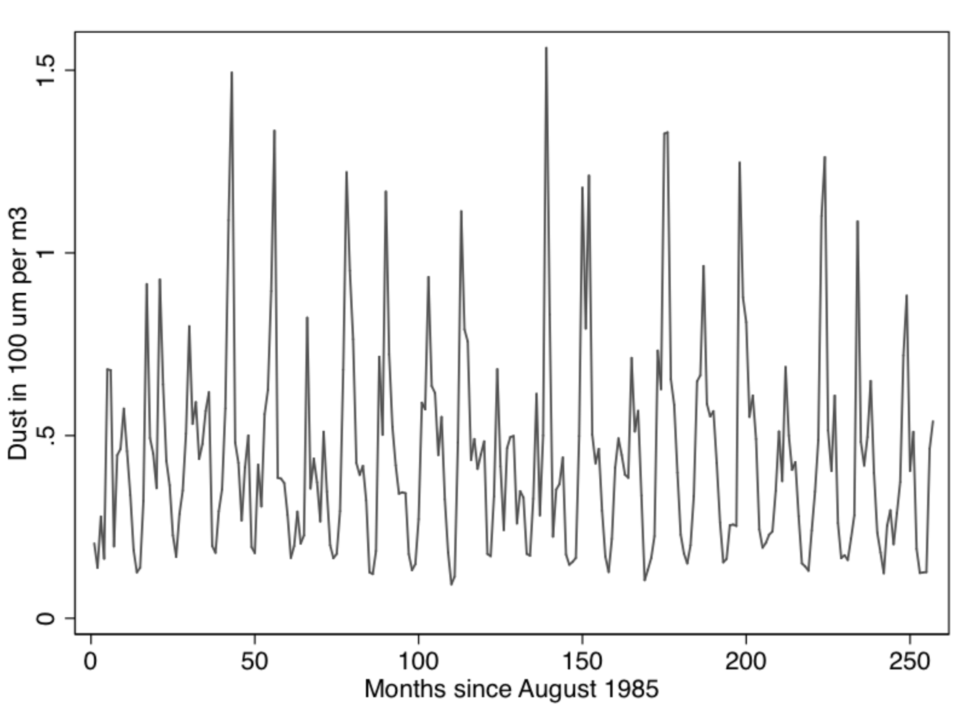
The square dots are DHS survey clusters. Shades of grey represent deciles of mean dust, ranging from dark (most dust) to light (least dust). The round dots are dust points.

Figure 2: Infant Mortality by Country



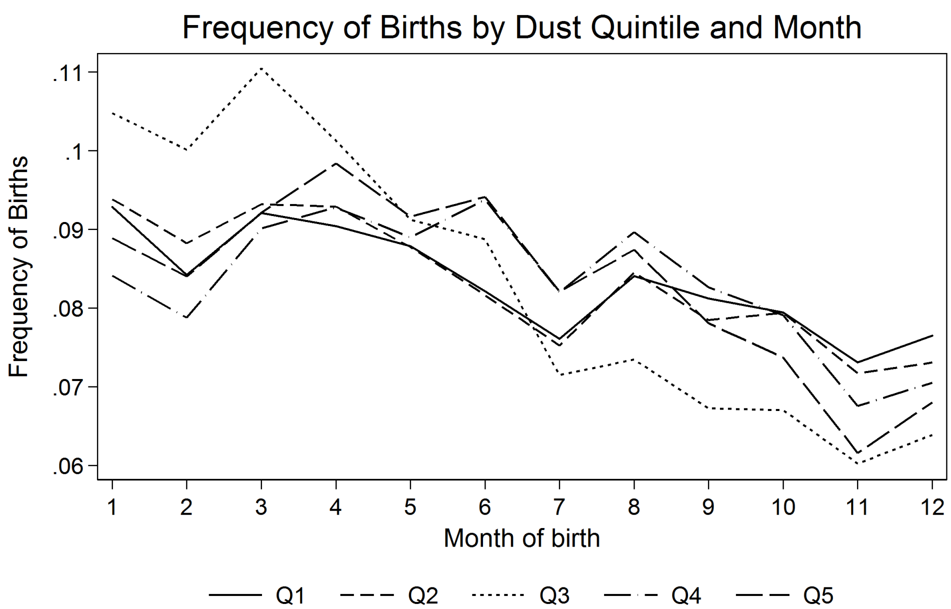
Graph shows infant death by year of birth and country. Infant mortality calculated from raw DHS data without adjustment. Country abbreviations are as follows: BF = Burkina Faso, BJ = Benin, CI = Ivory Coast, GH = Ghana, GN = Guniea, LB = Liberia, ML = Mali, NG = Nigeria, NI = Niger, SL = Sierra Leone, SN = Senegal, TG = Togo.

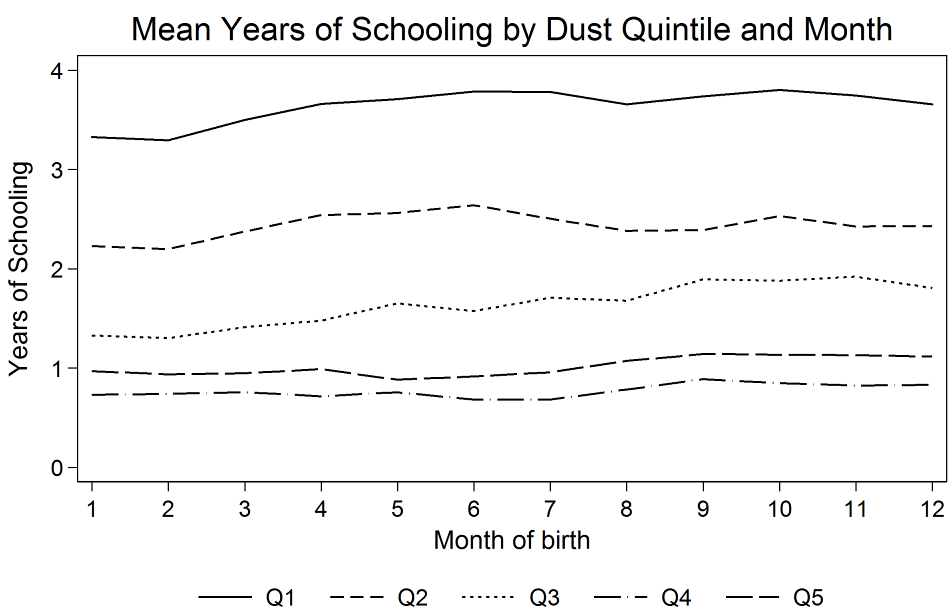
Figure 3: PM2.5



Graph shows PM2.5 concentrations averaged for the sample at the year and month level.

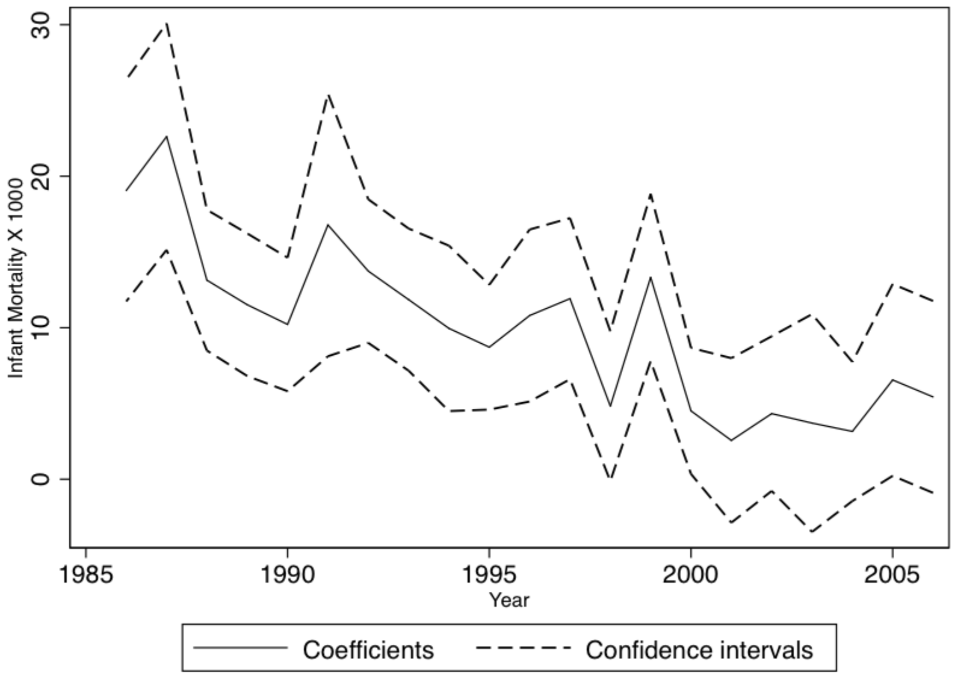
Figure 4: Tests for selective fertility





The top figure shows the percentage of total births that occur in a given month within each quintile of dust clusters. The bottom figure shows the average education of mothers whose births occur in a given month within each quintile of dust clusters.

Figure 5: Effects of dust over time



Equation (2) is estimated for each year and the coefficients on dust and associated confidence intervals are plotted.

Table 1. Summary Statistics

	(1) Mean	(2) s.d.	(3) Min	(4) Max	(5) N
Outcomes					
Died neonatal X 1000	54.6	227	0	1,000	615,187
Died as child X 1000	172	377	0	1,000	615,187
Died as infant X 1000	112	315	0	1,000	615,187
Treatment					
Dust L0 through L8 (cumulative) in 100s of micrograms/metercube	4.11	1.52	0.55	17.3	597,267
Environment Controls					
Mean Dust (in 100s of micrograms/metercube)	0.44	0.13	0.18	1.36	615,187
SD Dust	0.30	0.073	0.16	0.94	615,187
Child Controls					
Birth order	3.74	2.44	1	18	615,187
Multiple	0.035	0.18	0	1	615,187
Female	0.49	0.50	0	1	615,187
Mother Controls					
Mother Years of Education	1.63	3.35	0	22	614,827
Mother Age	25.9	6.60	9	50	615,187
Country Level Variables					
GNI per capita (in 2006 dollars)	589.77	943.76	160	5740	615,187
Health expenditure per capita (in 2006 dollars)	7.79	4.57	1	27	615,187

Table 2. Impacts of Dust on Mortality

	(1)	(2)	(3)	(4)	(5)	(6)
	Neonatal Mortality X 1000		*Infant Mortality X 1000*		*Child Mortality X 1000*	
Dust L0 through L8	0.151	0.209	2.061**	2.581***	3.141***	4.142***
	(0.599)	(0.650)	(0.846)	(0.854)	(1.137)	(1.142)
Observations	597,267	596,915	597,267	596,915	597,267	596,915
Country X Month of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes	Yes
DHS Cluster FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year of birth time trends	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Mean of Dependent Variable	***54.56***		***111.71***		***171.7***	

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by dust point in parentheses, unless otherwise indicated. All regressions are OLS. Controls are rainfall, temperature, rainfall and temperature interacted, rainfall and temperature squared, birth order, female, multiple, mother's age, mother's age squared, mother's years of education, and mother's religion, unless otherwise indicated.*

Table 3. Alternative Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Infant Mortality X 1000			
Dust L0 through L8	2.581***	2.395***	1.011	5.214***	3.524**	1.036	2.892**
	(0.854)	(0.874)	(1.015)	(1.301)	(1.624)	(4.164)	(1.231)
Observations	597,267	596,915	597,267	596,915	596,915	119,236	596,915
Mean of Dependent Variable				***111.71***			
				Child Mortality X 1000			
Dust L0 through L8	4.142***	3.898***	1.884	10.117***	8.150***	7.011	3.736**
	(1.142)	(1.268)	(1.277)	(1.762)	(1.991)	(4.667)	(1.589)
Observations	596,915	596,915	596,915	596,915	596,915	119,236	596,915
Mean of Dependent Variable				***171.7***			
Fixed effects	Country X Month of birth, Year of birth, DHS Cluster X Survey year, Country time trends	Country X Month of Birth, Year of Birth, Year of Survey X Country, Dust point ID, Country time trends	Country X Year of birth, Country X Month of birth, DHS Cluster X Year of Survey	Country time trends, Country X Month of birth,Year of Birth X Month of Birth, DHS Cluster X Year of Survey	Year of Birth X Month of Birth, Country X Year of birth, Country X Month of birth, DHS Cluster X Year of survey	Year of Birth X Month of Birth X Country of Birth, DHS cluster X Year of survey	Mother, Country X Year, Month
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by dust point in parentheses, unless otherwise indicated. All regressions are OLS. Controls are rainfall, temperature, rainfall and temperature interacted, rainfall and temperature squared, birth order, female, multiple, mother's age, mother's age squared, mother's years of education, and mother's religion, unless otherwise indicated.*

Table 4. Impacts of Dust After Birth

	(1)	(2)
	Infant Mortality X 1000	*Child Mortality X 1000*
Dust L0 through L8	3.330***	5.308***
	(1.033)	(1.206)
Dust: Birth to End of Period	0.996	3.086***
	(0.929)	(0.469)
Observations	572,397	572,397
Country X Month of Birth FE	Yes	Yes
Birth Year FE	Yes	Yes
DHS Cluster FE	Yes	Yes
Country X Year of birth time trends	Yes	Yes
Controls	Yes	Yes
Mean of Dependent Variable	***111.71***	***171.7***

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by dust point in parentheses, unless otherwise indicated. All regressions are OLS. Controls are rainfall, temperature, rainfall and temperature interacted, rainfall and temperature squared, birth order, female, multiple, mother's age, mother's age squared, mother's years of education, and mother's religion, unless otherwise indicated.*

Table 5. Heterogeneous Impacts of Dust on Mortality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Infant Mortality X 1000				
Dust: Month of Birth	2.338**	8.153***	2.498**	2.607***	2.931***	1.588	2.638**	2.309	2.482*
	(0.925)	(1.831)	(1.103)	(0.863)	(1.047)	(1.366)	(1.030)	(1.426)	(1.332)
Dust X Interaction Variable	0.492	-0.217***	0.110	-0.144	0.373	-0.419	-0.158	na	-0.254
	(0.567)	(0.059)	(0.966)	(0.465)	(0.481)	(1.105)	(0.825)		(1.070)
Observations	596,915	596,915	596,915	596,915	379,202	248,890	465,965	205,654	230,709
Mean of Dependent Variable					***111.71***				
					Child Mortality X 1000				
Dust: Month of Birth	3.365***	10.661***	3.295**	4.211***	3.585**	2.814	2.792**	4.165**	5.161***
	(1.201)	(2.381)	(1.525)	(1.154)	(1.432)	(1.882)	(1.407)	(1.795)	(1.688)
Dust X Interaction Variable	1.573**	-0.254***	1.104	-0.404	-1.824***	-0.991	2.781**	na	-0.785
	(0.685)	(0.073)	(1.181)	(0.584)	(0.648)	(1.269)	(1.085)		(1.316)
Observations	596,915	596,915	596,915	596,915	379,202	248,890	465,965	205,654	230,709
Mean of Dependent Variable					***171.7***				
Interaction Variable	Female	Mother Age	Rural	Any Education	Wealth Index	House has thatched roof	House has mud floor	Sample restricted to non-migrants	Woman works outside the home
Country X Month of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DHS Cluster FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year of birth time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by dust point in parentheses, unless otherwise indicated. All regressions are OLS. Controls are the un-interacted effect, rainfall, temperature, birth order, female, multiple, mother's age, mother's age squared, mother's years of education, and mother's religion, unless otherwise indicated.*

Table 6. Impacts of Dust on Early-life Investment Responses

	(1)	(2)	(3)	(4)	(5)	(6)
	Early-life investments					
	No. of Polio doses received	*No. of DPT doses received*	*Received Measles*	*No. of Total Vaccinations*		
Dust L0 through L8	0.058***	0.049***	0.022***	0.132***		
	(0.015)	(0.015)	(0.006)	(0.035)		
Observations	143,814	143,114	141,670	140,638		
Mean of dependent variable	***1.83***	***1.73***	***0.52***	***4.09***		
	At-birth investment responses					
	Received BCG Vaccination	*Received Polio 0 dose*	*Prenatal Doctor Visit*	*Home Delivery*	*Doctor Attended Delivery*	
Dust L0 through L8	0.007**	0.005	-0.001	0.002	-0.000	
	(0.003)	(0.004)	(0.002)	(0.002)	(0.001)	
Observations	146,250	122,344	116,698	150,966	150,559	
Mean of dependent variable	***0.71***	***0.46***	***0.077***	***0.56***	***0.034***	
	Eary life health outcomes					
	Arm Circumference / Age (percentile)	*Arm Circumference / Height (percentile)*	*Weight / Height (percentile)*	*Weight / Age (percentile)*	*Height / Age (percentile)*	*Birthweight*
Dust L0 through L8	0.807	-0.037	-0.980***	-1.821***	-1.880***	-0.011
	(0.917)	(1.272)	(0.311)	(0.368)	(0.328)	(0.007)
Observations	4,611	4,281	114,889	109,099	109,099	46,112
Mean of dependent variable	***26.3***	***34.05***	***34.17***	***21.24***	***23.84***	***3.14***
Country X Month of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes	Yes
DHS Cluster FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year of birth time trends	Yes	Yes	Yes	Yes	Yes	Yes
Child Recode Controls	Yes	Yes	Yes	Yes	Yes	Yes

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by dust point in parentheses, unless otherwise indicated. All regressions are OLS. Child recode controls are rainfall, temperature, rainfall and temperature interacted, rainfall and temperature squared, birth order, female, multiple, months between survey and birth, mother's age, mother's age squared, mother's years of education, and mother's religion, unless otherwise indicated.*

Table 7. Changes Over Time in Impacts of Dust on Mortality

	(1)	(2)	(3)	(4)
	Infant Mortality X 1000		*Child Mortality X 1000*	
Dust L0 through L8	7.262***	8.110***	13.919***	15.467***
	(1.204)	(1.256)	(1.782)	(1.990)
Dust X Time (Years)	-0.547***	-0.579***	-1.132***	-1.186***
	(0.086)	(0.089)	(0.144)	(0.150)
Observations	597,267	596,915	597,267	596,915
Country X Month of Birth FE	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes
DHS Cluster FE	Yes	Yes	Yes	Yes
Country X Year of birth time trends	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Mean of Dependent Variable	***111.71***		***171.7***	

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by dust point in parentheses, unless otherwise indicated. All regressions are OLS. Controls are rainfall, temperature, rainfall and temperature interacted, rainfall and temperature squared, birth order, female, multiple, mother's age, mother's age squared, mother's years of education, and mother's religion, unless otherwise indicated.*

Table 8. Interactions with Country level variables

	(1)	(2)	(3)	(4)
	Infant Mortality X 1000		*Child Mortality X 1000*	
Dust: Month of Birth	2.553*	3.178**	2.617	3.861**
	(1.335)	(1.327)	(1.681)	(1.748)
Dust X GNI per capita	-0.004***	-0.004***	-0.005**	-0.006**
	(0.001)	(0.001)	(0.002)	(0.002)
Observations	310,523	310,297	310,523	310,297
	Infant Mortality X 1000		*Child Mortality X 1000*	
Dust: Month of Birth	5.626***	6.947***	10.052***	12.311***
	(1.811)	(1.733)	(1.964)	(1.993)
Dust X Health expenditure	0.085	0.086	0.084	0.080
	(0.227)	(0.221)	(0.296)	(0.289)
Observations	292,555	292,352	292,555	292,352
Country X Month of Birth FE	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes
DHS Cluster FE	Yes	Yes	Yes	Yes
Country X Year of birth time trends	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Mean of Dependent Variable	***111.71***		***171.7***	

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by dust point in parentheses, unless otherwise indicated. All regressions are OLS. Controls are the un-interacted main effect, rainfall, temperature, squares of each, rainfall and temperature interacted, birth order, female, multiple, mother's age, mother's age squared, mother's years of education, and mother's religion, unless otherwise indicated. Bottom panel controls for GNI per capita and interaction of dust and GNI per capita.*

Table A1. Impacts of Dust on Mortality (robust to use of PM 10)

	(1)	(2)	(3)	(4)	(5)	(6)
	Neonatal Mortality X 1000		*Infant Mortality X 1000*		*Child Mortality X 1000*	
Dust L0 through L8	-0.051	-0.023	0.455**	0.626***	0.826***	1.150***
	(0.149)	(0.163)	(0.217)	(0.213)	(0.314)	(0.306)
Observations	594,735	594,385	594,735	594,385	594,735	594,385
Country X Month of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes	Yes
DHS Cluster FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year of birth time trends	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Mean of Dependent Variable	***54.56***		***111.71***		***171.7***	

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by dust point in parentheses, unless otherwise indicated. All regressions are OLS. Controls are rainfall, temperature, rainfall and temperature interacted, rainfall and temperature squared, birth order, female, multiple, mother's age, mother's age squared, mother's years of education, and mother's religion, unless otherwise indicated.*

Table A2. Impacts of Alternative Dust Measures on Mortality

	(1) *Infant Mortality X 1000*	(2) *Child Mortality X 1000*
Specification 1		
Number of past 9 months with above average dust	0.450	0.712
	(0.474)	(0.600)
Specification 2		
Number of past 9 months with above average dust + 1SD	1.679**	2.950***
	(0.659)	(0.869)
Specification 3		
Max of dust in the past 9 months	4.188**	5.656**
	(1.810)	(2.302)
Specification 4		
Log of dust in the past 9 months	9.454***	13.174***
	(3.316)	(4.568)
Specification 5		
Dust L0 through L8 (controlling for dust SD L0-L8)	2.305*	3.513*
	(1.390)	(1.938)
SD of dust L0-L8	2.652	6.048
	(9.453)	(13.023)
Specification 6		
Dust L0 through L8 (controlling for max dust L0-L8)	2.515*	4.684**
	(1.306)	(1.811)
Observations	596,915	596,915
Country X Month of Birth FE	Yes	Yes
Birth Year FE	Yes	Yes
DHS Cluster FE	Yes	Yes
Country X Year of birth time trends	Yes	Yes
Controls	Yes	Yes
Mean of Dependent Variable	***111.71***	***171.7***

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by dust point in parentheses, unless otherwise indicated. All regressions are OLS. Controls are rainfall, temperature, rainfall and temperature interacted, rainfall and temperature squared, birth order, female, multiple, mother's age, mother's age squared, mother's years of education, and mother's religion, unless otherwise indicated.*

Table A3. Impacts of Dust on Mortality - Inverse weighting and bilinear interpolation

	(1)	(2)	(3)	(4)
	Infant Mortality X 1000		*Child Mortality X 1000*	
Dust L0 through L8	2.769***	2.671***	3.783**	4.349***
	(0.995)	(0.855)	(1.612)	(1.151)
Weights	Inverse distance	Bi-linear interpolation	Inverse distance	Bi-linear interpolation
Observations	596,915	596,914	596,915	596,914
Country X Month of Birth FE	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes
DHS Cluster FE	Yes	Yes	Yes	Yes
Country X Year of birth time trends	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean of Dependent Variable	***111.71***		***171.7***	

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by dust point in parentheses, unless otherwise indicated. All regressions are OLS. Controls are rainfall, temperature, rainfall and temperature interacted, rainfall and temperature squared, birth order, female, multiple, mother's age, mother's age squared, mother's years of education, and mother's religion, unless otherwise indicated.*

Table A4 - Nonlinear effects of dust

	(1)	(2)
	Infant Mortality X 1000	*Child Mortality X 1000*
Dust L0-L8 decile 2	2.205	4.392*
	(2.061)	(2.411)
Dust L0-L8 decile 3	0.739	2.798
	(2.101)	(2.695)
Dust L0-L8 decile 4	6.309***	7.571***
	(2.300)	(2.902)
Dust L0-L8 decile 5	2.261	1.671
	(2.738)	(3.571)
Dust L0-L8 decile 6	2.181	2.423
	(3.012)	(3.662)
Dust L0-L8 decile 7	6.842**	6.611
	(3.156)	(4.033)
Dust L0-L8 decile 8	7.703**	8.666**
	(3.373)	(4.116)
Dust L0-L8 decile 9	6.076	5.656
	(3.715)	(4.688)
Dust L0-L8 decile 10	10.602**	13.375**
	(4.424)	(5.606)
Observations	596,915	596,915
Country X Month of Birth FE	Yes	Yes
Birth Year FE	Yes	Yes
DHS Cluster FE	Yes	Yes
Country X Year of birth time trends	Yes	Yes
Controls	Yes	Yes
Mean of Dependent Variable		

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by dust point in parentheses, unless otherwise indicated. All regressions are OLS. Controls are rainfall, temperature, rainfall and temperature interacted, rainfall and temperature squared, birth order, female, multiple, mother's age, mother's age squared, mother's years of education, and mother's religion, unless otherwise indicated.*

Table A5. Additional Robustness of Impacts of Dust on Mortality

	(1)	(2)	(3)
	Neonatal Mortality X 1000	*Infant Mortality X 1000*	*Child Mortality X 1000*
		Drop Highest Dust Decile Clusters	
Dust L0 through L8	-0.227	1.880*	2.035*
	(0.770)	(0.977)	(1.201)
Observations	537,274	537,274	537,274
		Drop Lowest Dust Decile Clusters	
Dust L0 through L8	0.117	2.355**	3.721***
	(0.709)	(0.945)	(1.232)
Observations	537,189	537,189	537,189
Country X Month of Birth FE	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes
DHS Cluster FE	Yes	Yes	Yes
Country X Year of birth time trends	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Mean of Dependent Variable	***54.56***	***111.71***	***171.7***

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by dust point in parentheses, unless otherwise indicated. All regressions are OLS. Controls are rainfall, temperature, rainfall and temperature interacted, rainfall and temperature squared, birth order, female, multiple, mother's age, mother's age squared, mother's years of education, and mother's religion, unless otherwise indicated.*

Table A6. Impacts of Dust on Mortality - clustered at regional level

	(1)	(2)	(3)	(4)
	Infant Mortality X 1000		*Child Mortality X 1000*	
Dust L0 through L8	2.061**	2.581***	3.141***	4.142***
	(0.895)	(0.952)	(1.187)	(1.409)
Observations	597,267	596,915	597,267	596,915
Country X Month of Birth FE	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes
DHS Cluster FE	Yes	Yes	Yes	Yes
Country X Year of birth time trends	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Mean of Dependent Variable	***111.71***		***171.7***	

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by DHS region in parentheses, unless otherwise indicated. All regressions are OLS. Controls are rainfall, temperature, rainfall and temperature interacted, rainfall and temperature squared, birth order, female, multiple, mother's age, mother's age squared, mother's years of education, and mother's religion, unless otherwise indicated.*

Table A7. Dust exposure and characteristics of children and mothers

	(1) Female	(2) Multiple birth	(3) Mother's age	(4) Any education	(5) Years of education	(6) Birth Order
Dust L0 through L8	-0.001	0.001	0.012	0.001	0.018*	-0.010
	(0.001)	(0.001)	(0.017)	(0.001)	(0.010)	(0.007)
Observations	597,267	597,267	597,267	596,915	596,915	597,267
Country X Month of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes	Yes
DHS Cluster FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year of birth time trends	Yes	Yes	Yes	Yes	Yes	Yes

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by dust point in parentheses, unless otherwise indicated. All regressions are OLS. Controls are rainfall, temperature, rainfall and temperature interacted, rainfall and temperature squared, unless otherwise indicated.*

Table A8. Impacts of Dust on Mortality by Trimesters

	(1)	(2)	(3)	(4)	(5)	(6)
	Neonatal Mortality X 1000		*Infant Mortality X 1000*		*Child Mortality X 1000*	
First trimester dust	0.845	0.747	3.363***	3.544***	4.451***	5.026***
	(0.783)	(0.790)	(1.241)	(1.224)	(1.582)	(1.584)
Second trimester dust	-0.825	-0.649	0.991	1.683	2.618*	3.749***
	(0.792)	(0.838)	(1.143)	(1.143)	(1.466)	(1.414)
Third trimester dust	0.582	0.620	2.055*	2.624**	2.542*	3.712***
	(0.911)	(0.952)	(1.090)	(1.103)	(1.362)	(1.358)
Observations	597,267	596,915	597,267	596,915	597,267	596,915
Country X Month of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes	Yes
DHS Cluster FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year of birth time trends	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Mean of Dependent Variable	***54.56***		***111.71***		***171.7***	

*Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by dust point in parentheses, unless otherwise indicated. All regressions are OLS. Controls are rainfall, temperature, rainfall and temperature interacted, rainfall and temperature squared, birth order, female, multiple, mother's age, mother's age squared, mother's years of education, and mother's religion, unless otherwise indicated.*