IMPACTS OF ENVIRONMENTAL DEGRADATION: FOREST LOSS, MALARIA, AND CHILD OUTCOMES IN NIGERIA

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July 31, 2018

[PRELIMINARY AND INCOMPLETE – PLEASE DO NOT CIRCULATE]

Abstract

We investigate how environmental degradation at the very beginning of child's life impacts childhood health. In particular, we examine the effect of forest loss around the time of birth on infant mortality and the early childhood health and nutrition of children in Nigeria. We geolink a new high-resolution data set of global forest loss (Hansen et al. 2013) to child-level data from the Nigeria Demographic and Health Surveys (DHS) from 2008 and 2013 and, given that location of forest loss is potentially nonrandom and that confounding economic trends may be associated with health outcomes, we employ several estimation strategies. We include geographic fixed effects, time-region trends, and several spatially dis-aggregated, time-variant and time-invariant controls from remote sensing data, to isolate the health effects using only within-LGA variation and, in some specifications, we use mother fixed effects to control for all time-invariant characteristics at a household level. We find that forest loss is associated with an increase in infant mortality – one standard deviation of forest loss is associated with a nine to 14 percent increase in the likelihood of death within the first month of life. In a separate analysis, we show that forest loss is associated with an increase in malaria incidence and, given that we have a panel of forest loss, we determine that the greatest malaria impact occurs in the year after forest loss. Combining these findings on the timing of forest loss and malaria incidence with our results on infant mortality suggests that the mechanism linking forest loss to infant death is maternal exposure to malaria when the child in utero.

Keywords: environmental degradation, deforestation, malaria, infant mortality, children's health, Nigeria. **JEL codes:** I12, I15, J14, O13, O15, Q23.

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Acknowledgements:

We are grateful to Trisha Singh, Elisa Gan, and Jonah Simon for excellent research assistance and to the seminar participants at Middlebury, Colby, and Vassar Colleges and Northeastern University for helpful comments and advice. RA funding was provided by Middlebury College.

Introduction

Environmental degradation impacts human lives in numerous ways. Those who rely on natural resources for livelihood lose sources of food, fiber, and income as forests and water bodies disappear and soils degrade. Those who live in cities with increasing air pollution and poor sanitation suffer from respiratory diseases and lowered productivity. Many of these impacts are contemporaneous; other impacts, however, may still be felt years and decades later. Often, most vulnerable populations are infants and young children, for whom environmental degradation is outside of their control.

In this paper, we investigate how environmental degradation at the very beginning of child's life impacts childhood health. In particular, we examine the effect of forest loss around the time of birth on infant mortality and the early childhood health and nutrition of children in Nigeria. Additionally, we demonstrate that the pathway of this impact is through increased incidence of malaria (but not of other infectious diseases such as diarrhea or acute respiratory diseases). In Nigeria, a country with considerable forest loss and high malaria transmission rates, young children are particularly vulnerable as they have yet to acquire immunity. Particularly severe cases (with severe anemia, hypoglycemia, or cerebral malaria) often result in child mortality. Milder malaria infections lead to poor health outcomes, and some evidence suggests may have longer-term impacts on education, fertility, and productivity (Cutler et al. 2010; Lucas 2010; Barreca 2010; Lucas 2013).

Forest loss causes both ecological changes (higher ground temperatures, increased puddle formation, elimination of species that prey on mosquito larvae, etc.) and human behavioral changes (increased human contact due to siting of settlements, migration, etc.) that lead to increased disease incidence (Yasuoka and Levins 2007; Pattanayak et al. 2006). A recent analysis of published field studies for 87 mosquito species from 12 countries demonstrates that deforestation is one of the main anthropogenic influences on malaria prevalence: 53 percent of mosquito species are associated with deforested habitats, of those 57 percent carry human pathogens (Burkett-Cadena and Vittor 2017).

In order to investigate the causal impact of forest loss on child outcomes, we geolink a new high-resolution data set of global forest loss to child-level data from the Nigeria Demographic and Health Surveys (DHS) from 2008 and 2013. Given that location of forest loss is potentially nonrandom and that confounding economic trends may be associated with health outcomes, we use several estimation strategies. We include geographic fixed effects (at local government area (LGA) level) and time-region trends to isolate the health effects using only within-LGA variation, as well as several spatial variables to control for potential causes of forest loss, and, in some specifications, we use mother fixed effects to control for all time-invariant characteristics at a household level.

We find that forest loss is associated with an increase in infant mortality – one standard deviation of forest loss is associated with a nine to 14 percent increase in the likelihood of death within the first month of life, and this impact is greater (11-15 percent) in rural areas. In a separate analysis, we show that forest loss is associated with an increase in malaria incidence (but not other infectious diseases) and given that we have a panel of forest loss, we are able to determine that the greatest malaria impact occurs in the year after forest loss. Combining these findings on the timing of forest loss and malaria incidence with our results on infant mortality suggests that the mechanism linking forest loss to infant death is maternal exposure to malaria when the child in utero. We also find evidence that forest loss leads to lower height-for-age among surviving children.

Our paper is broadly related to several strands of research. On the one hand, we contribute to the literature in economics that establishes the health burden of air and water pollution, and natural resource degradation, as well as to more recent work that looks at longer-term effects of environmental degradation (see Pattannayak and Pfaff (2009) and Greenstone and Jack (2015) for review). On the other hand, this paper contributes to the literature on the impact of exogenous conditions or "shocks" in childhood. In contrast to many papers that examine more unusual or extreme events in early life, such as Frankenberg and Thomas (2017), we focus on a type of early-life shock (environmental degradation and loss of forest) that is highly relevant to the lives of millions who live in areas with high rates of deforestation. In this regard, our paper echoes the findings of Sharon Maccini and Dean Yang (2009) who examine early-life rainfall shocks on health, education, and socio-economic outcomes in Indonesia.

Importantly, there are several features of this paper that distinguishes it from existing research. First, we examine environmental shocks in several periods before and after birth thus providing evidence on the precise timing of early shock exposure. As far as we are aware only few papers conduct such an examination; see, for example, Almond (2006) and Maccini and Yang (2009). Second, this paper is one of the first to quantify the effects of natural resource degradation and land use activities. Notably, Teevrat Garg (2016) demonstrates the impact of deforestation on increased malarial incidence in Indonesia and Berazneva and Byker (2017) offer similar findings in the context of Nigeria.

The paper proceeds as follows. Section I discusses the link between environmental degradation and infant mortality and early-life health and nutrition outcomes, as well as provides the Nigerian context. Section II describes the data sets we use, provides some descriptive statistics, and outlines our empirical methods. Section III presents the main results and section IV shows a variety of supplementary analyses. Section V concludes.

I. Environmental degradation, forest loss, and poor health

In utero and early childhood environments are detrimental to the development of human capabilities: they help shape child health, cognitive skills, and noncognitive abilities (Heckman 2007), and, therefore, are responsible for many socio-economic outcomes later in life (Almond and Currie 2011). A growing body of research demonstrates the importance of environmental conditions and experiences before the age of five and their persistent effects on health and human capital formation in adulthood. Prenatal factors include maternal health and nutrition (e.g., Almond 2006), economic shocks (e.g., van den Berg, Lindeboom, and Portrait 2006), and environmental factors (e.g., Chay and Greenstone 2003); while some of early childhood (starting at birth and ending at age five) factors are found in infections and other disease incidence, as well as poor nutrition.

Adverse environmental conditions and experiences are particularly prominent in developing countries. It is estimated that child undernutrition and intrauterine growth restriction are responsible for 2.2 million deaths among children under five globally (Victora et al. 2010) and over 200 million children under five in developing countries fail to reach their full developmental potential due to poverty, poor nutrition and health, and inadequate care (Grantham-McGregor et al. 2007). And although children from low- and middle-income countries are born with lengths and weights close to the international standards of the World Health Organization, their growth falters in the first years of life (Victora et al. 2010).

Some of the key factors responsible for childhood undernutrition and intrauterine growth restriction in developing countries have been found in poor maternal nutrition and infections, and early childhood infections such as malaria (Walker et al. 2007). High poverty rates and low per capita incomes, weak institutions, climatic conditions, and degrading environment expose mothers and their children to poor nutrition and health risks (S. K. Pattanayak and Pfaff 2009). Often, maternal and early childhood health risks are environmentally driven. Environmental quality, for example, is largely responsible for the burden of three main infectious diseases – diarrhea, malaria, and acute respiratory infections (empirical evidence is reviewed in Pattanayak and Pfaff (2009)). Air and water pollution are also substantial and their impacts on health are well documented (see Greenstone and Jack (2015) for a review of research that focuses on the relationship between pollution and health outcomes in developing countries).

When it comes to the impacts of land use activities on health, however, there is limited research. Agricultural expansion and timber extraction in the past 300 years, however, have led to a net loss of approximately seven to eleven million square kilometers of forest globally (Foley et al. 2005). Between 2000 and 2012 alone forest loss was over two million square kilometers (Hansen et al. 2013). Moreover, fuelwood collection, infrastructure development, and other land use activities have altered forest ecosystem conditions without necessarily changing forest cover area. These changes, often adverse, have been in terms of species composition, forest productivity, local meteorological conditions, and introduction of new pests and pathogens (Foley et al. 2005). As a result, for example, forest cover loss has been linked to increased malaria transmission and incidence in humans in Brazil (Olson et al. 2010), Malaysia (Fornace et al. 2016), and Indonesia (Garg 2016). We also find a large impact of forest loss on malaria in the context of Nigeria – one standard deviation of forest loss increases malaria incidence by around 4.5 percent in children under five years of age (Berazneva and Byker 2017).

We extend our previous work in Nigeria to examine the impacts of forest loss on childhood mortality and health. Nigeria presents an interesting case study. The country has experienced one of the biggest net losses in forest cover on the continent. Since 1990, the country has lost over 17 million hectares of forest and other wooded land area, with an average annual loss of 3.5 percent for forest and 5 percent for wooded land area (FAO 2015). Reasons for forest loss have been found in conversion of forest areas to agriculture, infrastructure development, urbanization, official and unofficial logging and fuelwood collection, as well as uncoordinated land use policy and weak enforcement (Usman and Adefalu 2010). Nigeria is also home to one-fifth of Africa's population and carries one of the highest disease burdens in the region. The World Health Organization (WHO) estimates 560 maternal deaths per 100,000 live births and 117 deaths per 1,000 live births for children under five in 2013 (WHO 2015).

Moreover, Nigeria's geography makes the climate suitable for malaria transmission throughout the country. While the malaria transmission season decreases from south to north of the country (7-12 month perennial in duration in most of the south and 4-6 months seasonal in the north), up to 97 percent of Nigerians are at risk of getting the disease (NPC/Nigeria, NMCP/Nigeria, and International 2012).[1] As a result, malaria in Nigeria is endemic and the country bears up to 25 percent of the malarial disease burden on the continent. It is estimated that malaria is responsible for about 11 percent of maternal mortality, up to 25 percent of infant mortality, and 30 percent of under-five mortality, leading to approximately 300,000 childhood deaths per year (NPC/Nigeria, NMCP/Nigeria, and International 2012).

II. Data and methodology

In this section, we describe the multiple datasets that we use followed by our empirical strategy.

Health data: Our individual-level data come from the Nigeria Demographic and Health Surveys (DHS) for 2008 and 2013 that are designed to provide population and health indicators at the national and state levels (NPC and ICF 2009, 2014). The primary sampling unit in the DHS data sets is a cluster and it is defined on the basis of enumeration areas from the 2006 Population Census frame. The clusters, both urban and rural, are chosen using a stratified multiple-stage cluster design in both 2008 and 2013 rounds; and a sample of 41 in 2008 and 25 in 2013 households is then selected to interview per cluster. All women between 15 and 49 years of age, who are either permanent residents of the households in the sample or visitors present on the night before the survey, are interviewed. Given the cross-sectional nature of the data sets (clusters are not the same in 2008 and 2013), we construct a two-period panel of local government areas (LGAs), the second smallest administrative units. The data we use, however, are at an individual (child or mother) level.

[1] The dominant vector species in Nigeria are *Anopheles gambiae* and *A. funestus*, while the dominant malaria parasite species is *Plasmodium falciparum*, accounting for over 95 percent of all reported cases (NPC/Nigeria, NMCP/Nigeria, and International 2012).

In order to establish the link between exposure to forest loss and children's outcomes, we use infant mortality and children's anthropometric measurements (see Table 1). Height and weight of all children under age five in the sample households were measured during the 2008 and 2013 DHS rounds in order to calculate three indices: height-for-age, weight-for-height, and weight-for-age. The indices are calculated using growth standards from the World Health Organization (WHO) 2006 Multicentre Growth Reference Study and are expressed in standard deviation units from the WHO 2006 study medians (WHO 2006; NPC and ICF 2014).

The height-for-age index reflects a long-term nutritional status and is not sensitive to recent, short-term changes in dietary intake. It is, however, affected by recurrent or chronic illness such as malaria at an early age. Children whose height-for-age Z-score (HAZ) is below minus two standard deviations from the median of the WHO 2006 reference population are classified as stunted (or chronically malnourished), and children whose HAZ is below minus three standard deviations are classified as severely stunted. While the height-for-age index represents the long-term effects of malnutrition and health shocks, the weight-for-height index captures current nutritional status and health. It picks up the failure to receive adequate nutrition in the period preceding the measurement which can be a result of insufficient food intake or a recent incidence of illness. Children whose weight-for-height Z-score (WHZ) is below minus two standard deviations from the median of the WHO 2006 reference population are classified as wasted (or acutely malnourished), and children whose WHZ is below minus three standard deviations are classified as severely wasted. Children with WHZ above two standard deviations from the reference median are classified as overweight. Weight-for-age consists of both height-for-age and weight-for-height, thus representing both chronic malnutrition (stunting) and acute malnutrition (wasting).[2] Figure 1 shows the distribution of HAZ and WHZ in the data.

In the second part of our analysis, where we examine the mechanisms through which forest loss impacts health, we use data on the incidence of the three main infectious diseases in Nigeria – malaria, acute respiratory infection (ARI), and diarrhea. For each child under five years of age, the prevalence of malaria is estimated by asking mothers whether their child had fever during the two weeks preceding the survey. The prevalence of ARI and diarrhea are estimated by asking mothers if their child had been ill with a cough accompanied by short, rapid

[2] The DHS data sets exclude biologically implausible values for Z-scores. Following the cut-offs recommended by the WHO, data are excluded if a child's HAZ is below -6 or above +6.

breathing or diarrhea, respectively, in the two weeks preceding the survey. Therefore, the data are based on the mother's perception of illness and in the 2008 and 2013 rounds are not verified by a medical examination. The data on fever, cough, and diarrhea incidence, however, have been found to serve as good proxies of actual diseases (see, for example, Okiro and Snow (2010)). And many children test positive for malaria (using rapid diagnostic tests and microscopy) without the presence of fever (NPC/Nigeria, NMCP/Nigeria, and International 2012), thus likely underestimating the incidence of malaria and therefore impact of forest loss.

In addition, the DHS data contain other individual- and household-level demographic and socio-economic variables that we use as controls in estimation. Table 1 provides summary statistics for the sample used in our analysis.

Forest loss and cover: The tree loss variable is from a dataset of global forest change based on time-series analysis of Landsat images with loss allocated annually (Hansen et al. 2013). Forest loss is defined as a change from a forest to non-forest state (or a stand-replacement disturbance), encoded as either 1 (loss) or 0 (no loss), for a spatial resolution of one arc-second per pixel, or approximately 30 meters per pixel at the equator. We link the tree loss data with the DHS data sets based on the reported longitude and latitude of the DHS clusters. The exact locations of clusters are, however, displaced to protect the confidentiality of the respondents. Rural locations are displaced by 0-5 kilometers (with one percent displaced by 0-10 kilometers) and urban locations are displaced by 0-2 kilometers (the displacement is a random direction and random distance process). Following the best practice guidelines outlined in Perez-Haydrich et al. (2013), we create a 5-km buffer zone for each DHS cluster. We then calculate the share of pixels with annual forest loss (equal to the number of pixels within the buffer zone with forest loss divided by the total number of pixels within the buffer) for each DHS cluster from 2000 to 2013. In addition, we use tree cover in 2000 variable. The variable is defined as canopy closure for all vegetation taller than 5 meters in height and encoded as the share of pixels with canopy closure in the 5-km buffer zone for each DHS cluster. Figure 2 shows the forest cover and loss data, as well as the 2008 and 2013 DHS clusters. Figure 3 zooms in on the state of Edo that experienced the greatest tree cover loss between 2001 and 2016. Figures 4 and 5 show annual loss for the year of the DHS interview and three years preceding for an urban DHS 2008 cluster and a rural DHS 2013 cluster in Edo, as examples of tree cover loss data. The rural and urban clusters are chosen based on a significant amount of tree cover loss.

Controls: Soil, Luminosity, Conflict, Roads and Pipelines, and Rainfall: In order to tease out the effects of forest loss on health outcomes, we need to control for confounding trends and potentially nonrandom location of deforestation. Forest loss in Nigeria has been attributed to agricultural encroachment, urbanization, infrastructure development, official and unofficial logging, and firewood collection (FAO 2015). Therefore, we use several additional spatial data sets in our analysis.

Soil: Conversion of forest to agriculture is more likely on the land with high agricultural potential. Firewood collection may also be greater in densely populated agricultural villages. To capture agricultural development, we include soil fertility indicators from the Africa Soil Information Service (AfSIS), publicly available geo-referenced soil data at 250-meter spatial resolution (Hengl et al. 2015). The AfSIS data are available at different depths; we take the average of 0-5cm and 5-15cm depths in each 5-km buffer zone around the DHS clusters for three soil fertility indicators: soil organic carbon content (% by weight), soil pH (1-7), and Cation Exchange Capacity (CEC) (meq/100g). The three indicators have been used to reflect soil fertility: soil organic carbon corresponds to soil organic matter content that can be influenced by farm management practices and is therefore more transient; soil pH and CEC are related to soil texture and mineralogy and are more constant indicators of soil fertility (Sparks 1996).

Luminosity: Economic development in general and urbanization in particular have also been linked to deforestation. If malaria is more prevalent in areas with greater economic development, we need to control for this confounding factor. We use annual luminosity data that have been found to be a useful disaggregated proxy for economic activity in regions with low data quality (Chen and Nordhaus 2011). The luminosity data reflect the nighttime lights from cities, towns, and other sites with persistent lighting and are from the National Oceanic and Atmospheric Administration-National Geophysical Data Center (US Air Force Weather Agency 2009). We use the Version 4 of the DSMP-OLS Nighttime Lights Time Series, at a resolution of 30 arc-seconds and constructed using the smoothed spatial resolution mode, and calculate the annual average of nighttime lights in each 5-km buffer zone around the DHS clusters.

Conflict: Conflict – whether over pipeline development or due to Boko Haram activity – may also drive forest loss. The conflict data we use are from the Armed Conflict Location and Event Data Project (ACLED) that is available from 1997 to 2015 (Version 6) and records nine types of geocoded conflict events from a range of sources, including local and national media, agencies, NGOs and international organizations (Raleigh et al. 2010). Of the available event types, we create three categories: battle (ACLED events "battle – no change of territory," "battle – non-state actor overtakes territory," and "battle – government regains territory"), output conflict (ACLED events "riots/protests" and "violence again civilians), and remote violence (ACLED even "remote violence"). Following McGuirck and Burke (2017), output conflict category is to capture incidences of food riots, farm raids and crop theft, as well as general looting and rioting – conflict over the appropriation of surplus; while battle category is to reflect conflict over the control of territory. Remote violence category includes events where a spatially removed group determines the time, place and victims of the attack, such as bombings, mortar and missile attacks, and others. Boko Haram conflict activity is included in each of the categories, depending on incidence. For each category, we create an intensity of conflict variable that is equal the number of the events in a 5-km buffer year. While the ACLED data set also estimates the number of fatalities, the fatalities data are vulnerable to bias and inaccurate reporting; therefore, we do not use the fatalities data in our analysis. No fatalities are necessary for events to be included in the ACLED data set.

Roads and pipelines: Infrastructure and access to transportation affect migration and economic conditions in DHS clusters. To capture these effects, we calculate the distance from each DHS cluster to the nearest major road. The road data set comes from Natural Earth, supported by the North American Cartographic Information Society.[3] The "basic" roads at 10m (version 4.0.0) are not distinguished by type. They may include, but are not restricted to, tollways, freeways, primary roads, secondary roads, and paved roads. Our pipeline dataset "West African Existing and Proposed Pipelines" comes from The FracTracker Alliance.[4] We calculate the geodesic distance between a DHS cluster point and the nearest existing pipeline.

Rainfall: We use precipitation data to control for climatic variations that may correlate with malaria's spread. Our monthly and annual rainfall data come from Climate Hazards Group InfraRed Precipitation with Stations data (CHIRPS), a gridded rainfall time series dataset in 0.05-degree resolution (Funk et al. 2015). We use the African monthly and the world annual subset of CHIRPS (V2.0), which cover data from 1981 to 2018, and calculate the monthly and

[3] https://www.naturalearthdata.com/downloads/10m-cultural-vectors/roads/
[4] http://www.arcgis.com/home/item.html?id=79e940c72bef40709d131319b24001d7

annual average of precipitation in each DHS buffer zone. The average precipitation of the interview month is matched to each individual.

Econometric models: We use several estimation strategies to account for potentially nonrandom location of forest loss and confounding economic trends that may make it difficult to distinguish the effects of environmental degradation on health outcomes. We include fixed effects at the LGA level and time-region trends to isolate the health effects using only within-LGA variation. We also include several cluster-level, time-variant and time-invariant variables to control for potential causes of forest loss, as well as individual, mother, and household controls. Finally, in some specifications we use mother fixed effects to control for all time-invariant characteristics at a household level.

In order to examine the impact of forest loss on infant mortality and child anthropometrics we estimate the following equation:

$$(1) \qquad Y_{itc} = \alpha + \sum_{a=-2}^{0} \beta_a loss@age_{itc}^{a} + \gamma' Birth\_month_{itc} + \boldsymbol{Birth\_year'_t \delta}$$
$$+ \sum_{m=1}^{12} \zeta_m Birth\_month_{itc}^{m} \; x \; Region_c x \; Birth\_Year_t + \boldsymbol{LGA'_c \eta} + \boldsymbol{X'_{itc} \theta} + \; \epsilon_{itc},$$

where Y_{itc} is a health outcome for child *i* in DHS year *t* in cluster *c* (infant mortality, HAZ, or WHZ) and β_a provides estimates of the impact of tree loss for two years before and two years after child's year of birth, as discussed below. $Birth\_month_{itc}$ is the month of birth, $Birth\_year_t$ is the year of birth, and $\sum_{m=1}^{12} \zeta_m Birth\_month_{tc}^{m} \; x \; Region_c x \; Birth\_Year_t$ provides controls for regional weather and annual variation in seasonality. LGA_c is a set of LGA-fixed effects, and the vector $\boldsymbol{X'_{itc}}$ includes a rich set of individual-, mother-, and household-level controls, as well as cluster-level spatial data.[5] ϵ_{itc} is a mean-zero error term. We cluster standard errors at the LGA level and account for stratification used in the DHS sampling design.

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[5] Controls from DHS include indicator for a rural or urban location, number of household members, number of children under 5, time to drinking water source, indicator for toilet, floor, firewood collection, household head age and years of education, wealth quintile; mother's age, years of education, number of children, number of living children residing with mother, religion (Christian, Muslim, Yoruba, Igbo, Hausa), marital status, indicator for working outside of household, body mass index; and child's gender, birth interval, indicator for twin, and

Our variable $loss@age^{a}_{itc}$ is child-specific. For each child in both 2008 and 2013 DHS clusters, we have five forest loss variables: forest loss two years before birth (*loss-2*), one year before birth (*loss-1*), in child's year of birth (*loss 0*), first year after birth (*loss+1*), and second year after birth (*loss+2*). While we know the month of birth, our forest loss variable is at an annual scale, so forest loss in 2008 is forest loss that is detected primarily in the year 2008. However, for a child born in January of 2008 who spent most of in utero in 2007 *loss 0* should be loss in 2007, while for a child born in December of 2008 *loss 0* should be loss in 2008. We assign the year of loss as the calendar year in which a child spends her/his first trimester in utero. Therefore, forest loss in 2008 as *loss 0* corresponds to children born from August to December of 2008 and from January to July of 2009 (see Figure 6).

For specifications with mother fixed effects we estimate the following equation:

$$(2) \qquad Y_{imtc} = \alpha_m + \sum_{a=-2}^{0} \beta_a loss@age^{a}_{itc} + \gamma' Birth\_month_{itc} + \boldsymbol{Birth\_year'_t\,\delta}$$
$$+ \textstyle\sum_{m=1}^{12} \zeta_m Birth\_month^{m}_{itc}\ x\ Birth\_Year_t + \boldsymbol{Y'_{imtc}\theta} + \ \epsilon_{imtc}.$$

In this specification, Y_{imtc} is a health outcome for child *i* born to mother *m* in DHS year *t* in cluster *c* and α_m is mother fixed effects. All mother- and household-level controls, as well as cluster-level time-invariant spatial controls, are no longer needed as mother fixed effects absorb all time-invariant observable and unobservable characteristics. $\boldsymbol{Y'_{imtc}}$ includes child-level controls (gender, birth interval, and indicator if twin) and time-variant spatial cluster-level data (nighttime lights and conflict). Estimation of β_a relies only on the variation in forest loss over time at a household level.

While deforestation may impact health outcomes, the mechanism for this link is not clear. Finally, we return to our estimation of the impact of forest loss on disease incidence from Berazneva and Byker (2017) and estimate the following equation:

breastfeeding. Spatial controls include soil fertility indicators, nighttime lights data, conflict data, roads and pipelines, and rainfall data.

$$(3) \qquad Y_{itc} = \iota + \sum_{j=-3}^{0} \kappa_j loss_{tc}^{j} + \mu' month_{itc} + \boldsymbol{DHSyear'_t \nu}$$

$$+ \sum_{m=1}^{12} \xi_m month_{tc}^{m} \ x \ Region_c x \ DHSYear_t + \ \boldsymbol{X'_{itc}\lambda} + \boldsymbol{LGA'_c\pi} + \rho_{itc},$$

which is similar to equation 1 above but here Y_{itc} refers to a health outcome for child i in DHS year t in cluster c – incidence of malaria, acute respiratory infection, or diarrhea. $month_{tc}^{m}$ is the month of the interview and $DHSyear_t$ accounts for the round of the DHS survey, $\sum_{m=1}^{12} \xi_m month_{tc}^{m} \ x \ Region_c x \ DHSYear_t$ provides controls for regional weather and annual variation in seasonality that may influence the prevalence of infectious diseases. Since the incidence of malaria comes from asking mothers whether their child had fever during the two weeks preceding the survey, the sample size is different, and some controls are no longer used.

III. Main empirical results

Impact of forest loss on children's health

Table 2 gives estimates of the impact of forest loss on infant mortality. The unit of observation is live births for children who would have been under 60 months of age at the time of the DHS survey. The outcome is an indicator for whether the child died within the first month after birth. Nearly four percent of infants in the sample die within the first month. Column 1 gives estimates from estimating equation (1) with no controls, while the estimate in column 2 includes the full set of controls including LGA and year fixed effects and controls for seasonality, precipitation, soil, altitude, roads, pipelines, economic activity proxied by nighttime lights, and conflict. The magnitude of the statistically significant positive coefficient on forest loss two years prior to birth implies that one standard deviation of forest loss is associated with an 8.8 percent increase in the likelihood of death within the first month. Because the majority of mothers in the sample have had multiple births in the last 60 months, we can estimate an equation including mother fixed effects controlling for all time-invariant observed and unobserved variables at a very local level – the household. In this specification, we continue to control for time-varying factors such as economic activity, and conflict as well as seasonality of birth and general time trends. The coefficient in the mother-fixed effects specification in column 3 slightly increases to 14.2 percent and remains statistically significant. Note that the impact of forest loss on infant mortality comes from loss two year prior to the child's birth. We will discuss how this timing potential relates to gestational age below.

Table 3 reports results from estimating equations (1) and (2) where the dependent variables are height-for-age and weight-for-height z-scores among children under the age of 60 months. In columns 1 and 4, which give estimates from regressions with no controls, we see that, in the aggregate, forest loss is associated with better health—the correlation between forest loss and z-scores is positive and statistically significant. There are many factors, however, that may be correlated with both deforestation and health that potentially bias these initial estimates. Controlling for time-invariant differences across localities (LGAs) as well as time-varying controls related to the causes of deforestation such as soil type and economic activity, we see that in column 2 the coefficients on weight-for-height and height-for-age become negative, small and statistically insignificant. When we control for mother fixed effects in column 3, the coefficient on forest loss a year prior to birth becomes negative and significant for height-for-age (but not the shorter-term measure weight-for height), suggesting a negative impact of forest loss on height-for-age.

Impact of forest loss on infectious diseases

In previous work, Berazneva and Byker (2017), we explored the causal relationship between forest loss and disease incidence. We extend that work here in order to explore the mechanism behind our findings on the impact of forest loss on infant mortality and child height. As can be seen in columns 1, 4 and 7 in Table 4, we again find that there is a strong correlation between forest loss and better health—forest loss in the uncontrolled regressions is associated with statistically significantly lower incidence of malaria, diarrhea and cough. However, once we control for local area fixed effects and time-varying controls tied to the potential causes of forest loss, we find that the coefficient on malaria incidence turns negative and significant, while the coefficients on diarrhea and cough become small and insignificant. Because we have a panel of forest loss, we can include lags of forest loss allowing us to investigate the dynamic impact of forest loss on malaria. The greatest impact on malaria is from loss in the prior year with continuing impacts in the second year after which the effect declines to zero. This pattern is consistent with a temporary ecological disturbance and is consistent with the tropical medicine literature.

Given these estimates of the timing of malaria after forest loss, we return to the estimates in Tables 2 and 3. Columns 2 and 3 in Table 2 show that forest loss two years prior to birth is associated with higher risk of death in the first month. If malaria increases a year after forest loss, the implication is that forest loss two years prior to birth increases malaria incidence in the locality when the baby is in utero and that maternal exposure to malaria while pregnant is increasing infant mortality. Similar reasoning suggests that based on Table 3, malaria exposure in the year of birth leads to lower height-for-age in the subsequent years.

IV. Supplementary analyses

In continuing work, we will explore whether the impacts of forest loss vary by urban vs. rural status, whether health impacts are different for boys and girls, and if and how health impacts vary by child's age. We will also do several robustness checks (e.g., change buffer zones around the DHS clusters and include lags of forest loss as placebo) to assure the validity of our results.

V. Conclusion

This paper finds that children's health and nutrition are highly sensitive to the environmental degradation they experience in utero and early in life. We examine the effect of forest loss around the time of birth on infant mortality and the early childhood health and nutrition of children born in the 21st century Nigeria. Forest loss has positive effects on infant mortality – one standard deviation of forest loss is associated with a seven to a nine to 14 percent (depending on the specification) increase in the likelihood of death within the first month of life. We also find evidence that forest loss leads to lower height-for-age among surviving children.

The most plausible explanation for these results is that forest loss has a positive impact on malaria incidence. In a separate analysis, we show that forest loss is associated with an increase in malaria incidence and, given that we have a panel of forest loss, we determine that the greatest malaria impact occurs in the year after forest loss. Combining these findings on the timing of forest loss and malaria incidence with our results on infant mortality suggests that the mechanism linking forest loss to infant death is maternal exposure to malaria when the child in utero.

These results have important implications for policy. Our findings point to a group – infants in the rural areas – that is particularly vulnerable to environmental degradation. Nigeria's considerable forest loss and malaria incidence have the greatest impacts on infants in rural areas who are yet to acquire immunity. Severe cases of malaria result in child mortality; milder cases may have longer-term impacts on education, fertility, and productivity (Cutler et al. 2010; Lucas 2010; Barreca 2010; Lucas 2013). The short-term (mortality) and long-run health (stunting) effects of forest loss, therefore, should be factored into benefit-cost analyses of programs targeting this subpopulation. Our findings provide additional justification for interventions – for example, forest conservation policies and their enforcement to reduce forest loss and distribution of insecticide-treated nets and indoor residual spraying to prevent malaria – that safeguard infants from the health consequences of environmental shocks.

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Figure 1. Height-for-age and weight-for-height for children in the sample.

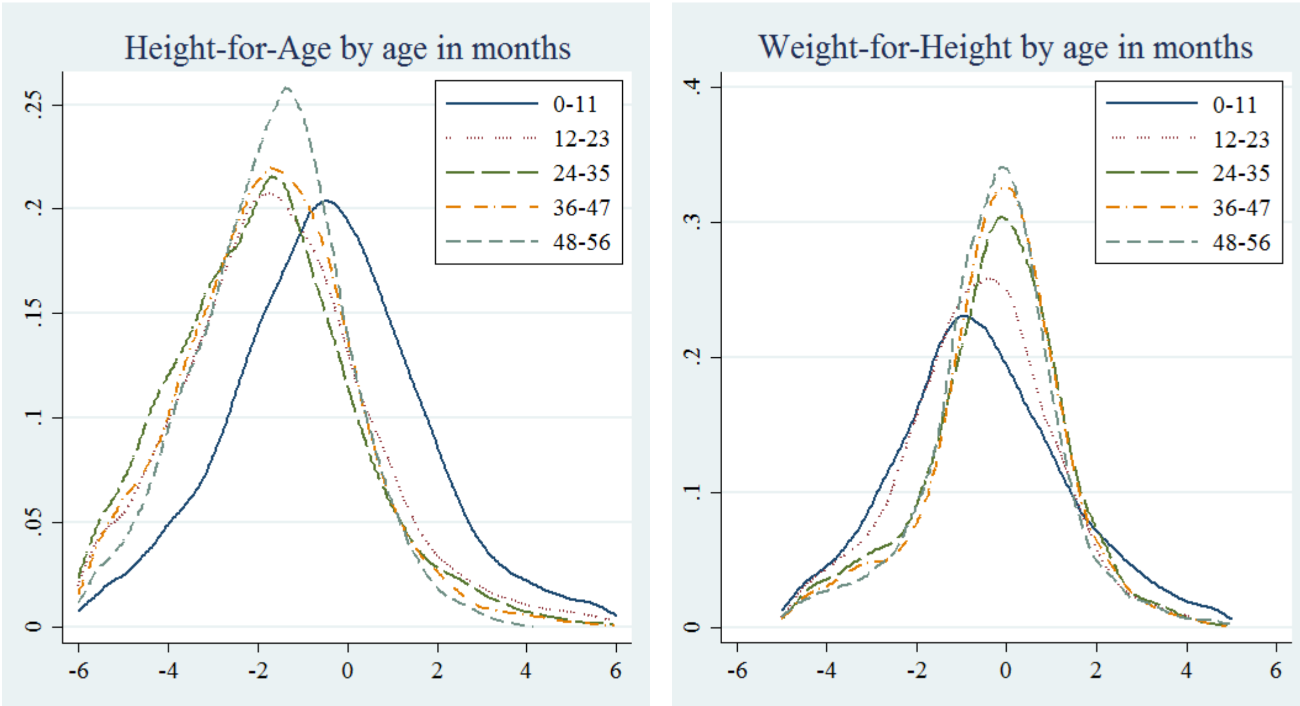
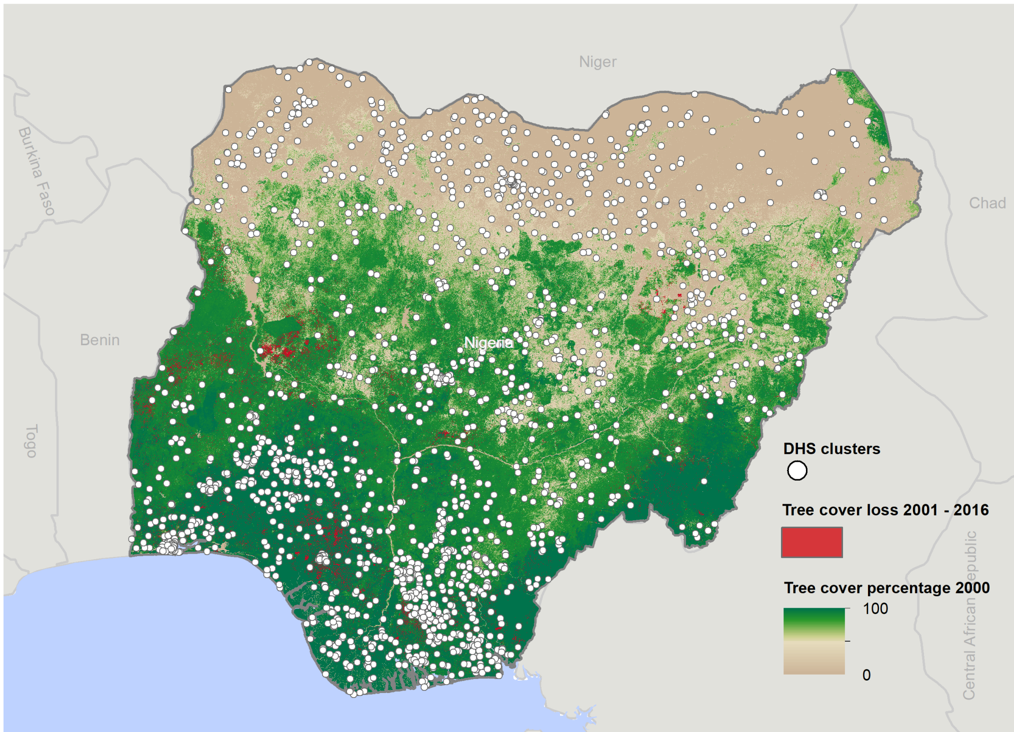
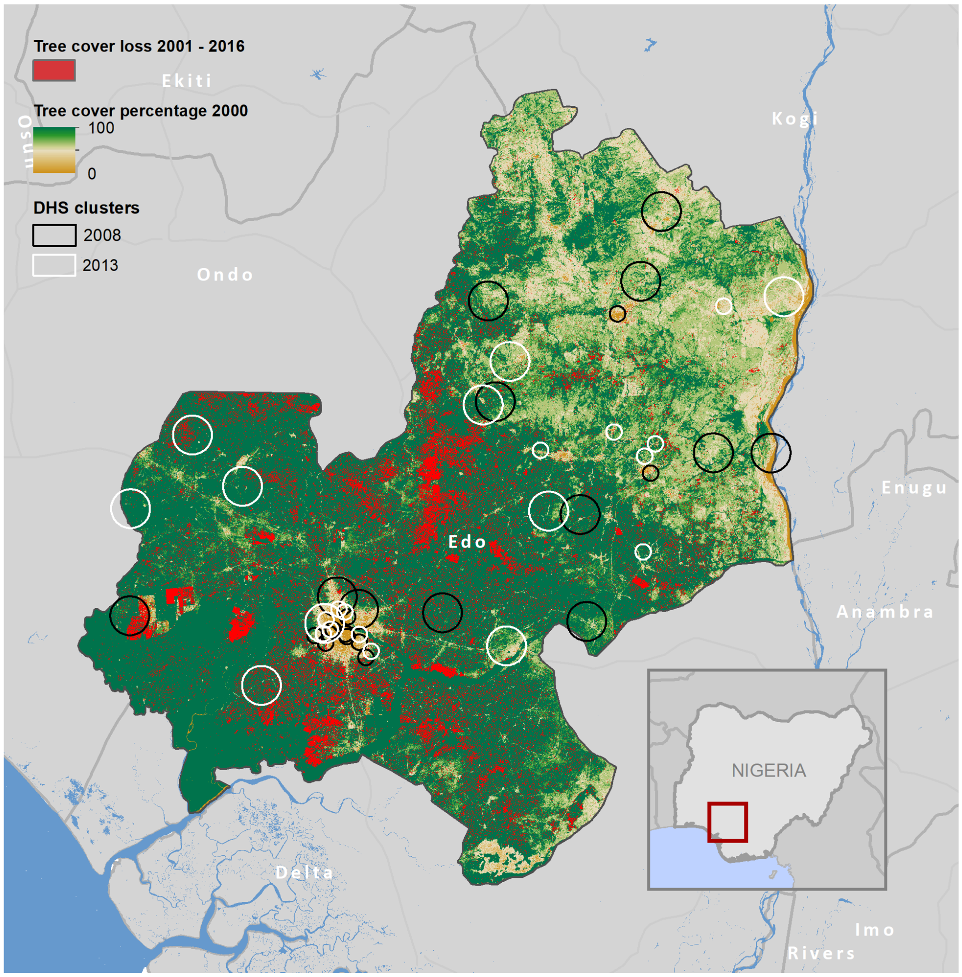


Figure 2. Tree cover in 2000 and tree cover loss from 2001 to 2016 in Nigeria.



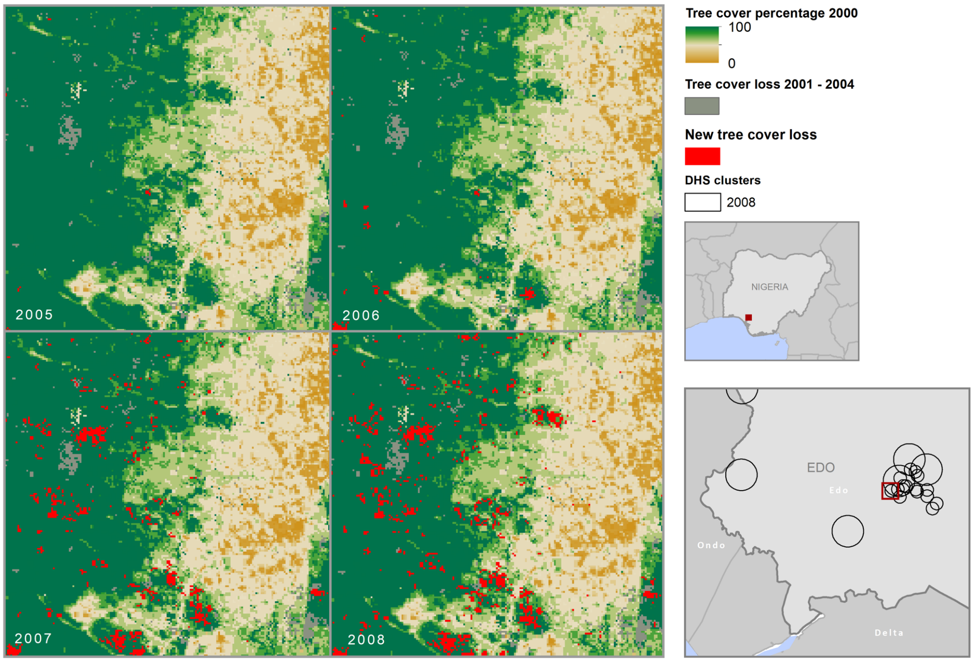
Source: Author's calculations based on forest loss data from Hansen/UMD/Google/USGS/NASA.

Figure 3. Tree cover in 2000 and tree cover loss from 2001 to 2016 in Edo state, Nigeria.



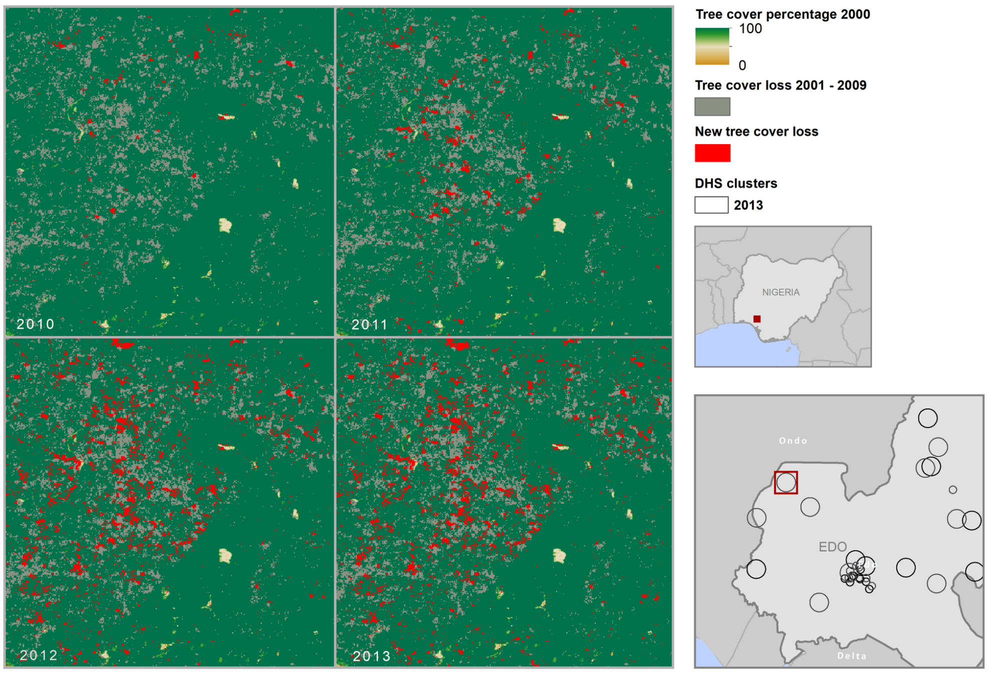
Source: Author's calculations based on forest loss data from Hansen/UMD/Google/USGS/NASA.

Figure 4. Tree cover in 2000 and tree cover loss from 2001 to 2004 for a representative urban DHS 2008 cluster in Edo state, Nigeria.



Source: Author's calculations based on forest loss data from Hansen/UMD/Google/USGS/NASA.

Figure 5. Tree cover in 2000 and tree cover loss from 2010 to 2013 for a representative rural DHS 2013 cluster in Edo state, Nigeria.



Source: Author's calculations based on forest loss data from Hansen/UMD/Google/USGS/NASA.

Figure 6. Assignment of forest loss to individuals.

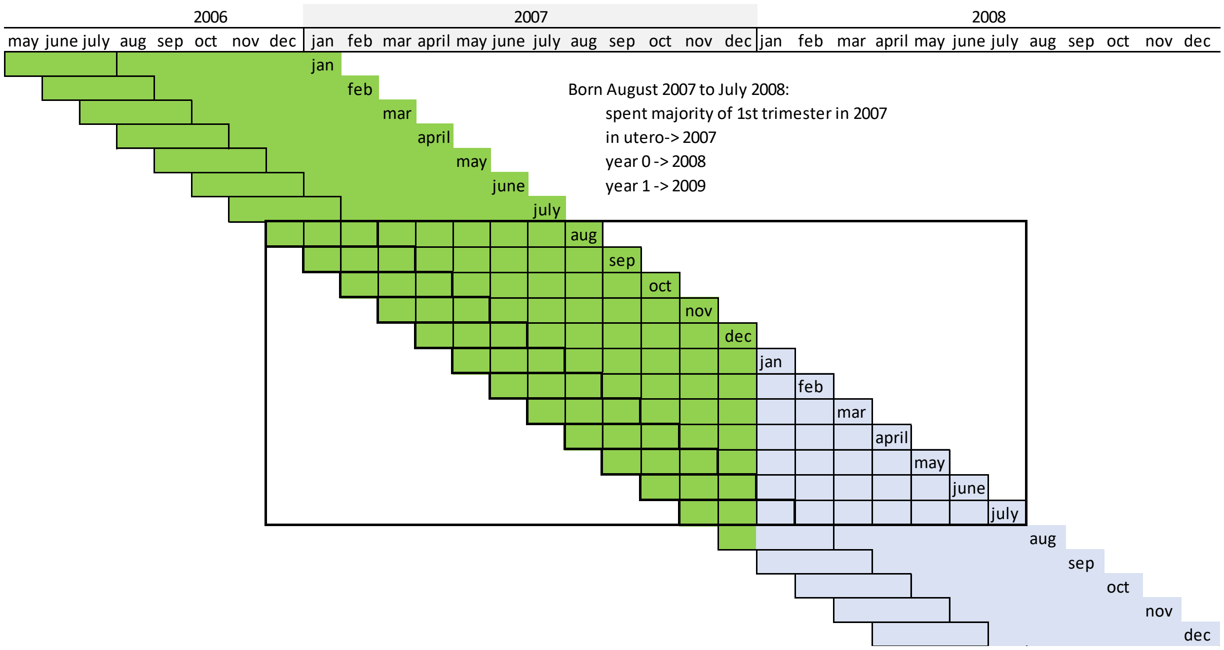


Table 1. Summary Statistics: Nigeria Demographic and Health Survey, Hansen et al. tree cover loss

DHS Wave	2008			2013		
	mean	sd	max	mean	sd	max
Mortality						
Died in first month	0.040			0.037		
Died before 59 months	0.111			0.090		
Observations	27,113			31,209		
Disease: proportion with symptoms in last 2 weeks:						
Fever	0.162			0.127		
Diarrhea	0.103			0.103		
Cough	0.124			0.098		
Age in months	27.8	17.2	59.0	28.5	17.3	59
Rural	0.69			0.64		
Use firewood for fuel?	0.76			0.74		
Slept under bednet	0.10			0.16		
Observations	24,077			28,042		
Forest loss: proportion of 5 km buffer lost since previous year						
This year	0.0009	0.0023	0.0533	0.0013	0.0037	0.0526
Last year	0.0011	0.0032	0.0533	0.0010	0.0026	0.0369
Two years ago	0.0005	0.0013	0.0888	0.0009	0.0030	0.0388

Table 2: Estimated Impact of Forest Loss on Infant Mortality

	Dependent variable: Died in first month of life					
	Full Sample			Rural Sample		
	(1)	(2)	(3)	(1)	(2)	(3)
Forest loss at:						
age_p_2	1.332**	1.558***	2.522**	1.467**	2.036***	2.831**
	(0.599)	(0.533)	(1.218)	(0.737)	(0.641)	(1.344)
age_p_1	-0.197	0.210	-0.850	-0.394	0.529	0.337
	(0.358)	(0.369)	(0.823)	(0.369)	(0.389)	(0.753)
age_0	-0.667	-0.347	-0.822	-0.537	-0.282	-0.652
	(0.475)	(0.455)	(0.973)	(0.515)	(0.488)	(0.958)
LGA fixed effects	no	yes	yes	no	yes	yes
Year fe, seasonality, weather	no	yes	yes	no	yes	yes
HH and indiv controls	no	yes		no	yes	
Soil, altitude, roads, pipelines	no	yes		no	yes	
Nighttime lights, conflict	no	yes	yes	no	yes	yes
Mother fixed effects	no	no	yes	no	no	yes
Observations	58,322	58,322	58,322	40,836	40,836	40,836
R-squared	0.000	0.113	0.021	0.000	0.120	0.023
Month_0 mortality rate		3.83%	3.83%		4.14%	4.14%
Impact of 1sd of forest loss two years prior to birth on likelihood of death as percentage of mortality rate		8.79%	14.22%		10.67%	14.84%

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3: Estimated Impact of Forest Loss on Child Biometrics

Dependent variable	Height-for-Age				Weight-for-Height			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Forest Loss at:								
age_p_2	34.45***	-4.535	-1.756	-10.45	-3.163	-2.957	-4.304	-1.531
	(11.48)	(4.624)	(9.031)	(10.96)	(7.821)	(5.527)	(8.234)	(9.925)
age_p_1	32.69***	-3.239	-14.07**	-20.52**	15.04***	5.431	6.439	6.427
	(8.824)	(5.167)	(6.968)	(8.082)	(5.245)	(3.750)	(6.799)	(8.016)
age_0	31.06***	-5.553	1.980	5.337	13.69**	3.351	-5.032	-5.369
	(7.909)	(4.905)	(6.972)	(8.000)	(5.452)	(4.995)	(6.696)	(7.586)
LGA fixed effects	no	yes			no	yes		
Year fixed effects	no	yes	yes	yes	no	yes	yes	yes
Seasonality	no	yes	yes	yes	no	yes	yes	yes
HH and indiv controls	no	yes			no	yes		
Soil and altitude	no	yes			no	yes		
Nighttime lights	no	yes	yes	yes	no	yes	yes	yes
Conflict	no	no	yes	yes	no	no	yes	yes
Mother fixed effects	no	no	yes	yes	no	no	yes	yes
Rural Sample				X				X
Observations	43,079	42,252	43,079	29,227	43,079	42,252	43,079	29,227
R-squared	0.040	0.253	0.253	0.299	0.007	0.159	0.115	0.145
Mean z-score	-1.42		-1.42	-1.66	-0.47			
Impact of 1sd of forest loss in year of birth	-0.072		-0.031	-0.063	0.033			

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4: Estimated Impact of Forest Loss on Disease Incidence among Children

Dependent variable	Malaria (Fever)			Diarrhea			Respitory (Cough)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Forest Loss									
this year	0.970	0.437	0.812	-1.440**	-0.699	-0.477	1.672	-1.067	-0.999
	(0.870)	(0.961)	(0.983)	(0.612)	(0.566)	(0.617)	(1.124)	(1.066)	(1.025)
1 year ago	-3.780***	1.981**	1.948**	-3.439***	0.622	0.726	-1.925**	0.258	0.264
	(1.219)	(0.938)	(0.933)	(1.123)	(0.603)	(0.634)	(0.946)	(0.778)	(0.758)
2 years ago	-1.152	0.990	0.521	0.501	0.349	0.117	-2.126**	-1.209	-1.155
	(1.324)	(0.933)	(1.016)	(1.612)	(1.016)	(0.950)	(0.985)	(0.835)	(0.841)
3 years ago	0.531	-3.162	-3.091	-6.099***	-0.123	-0.439	6.104**	0.417	0.730
	(2.113)	(2.467)	(2.490)	(1.252)	(1.063)	(1.172)	(2.853)	(2.082)	(2.007)
LGA fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year fixed effects, seasonality	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
HH and indiv controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Soil, altitude, weather	No	No	Yes	No	No	Yes	No	No	Yes
Nighttime lights, roads, pipelines	No	No	Yes	No	No	Yes	No	No	Yes
Conflict	No	No	Yes	No	No	Yes	No	No	Yes
Observations	52,119	52,119	52,092	52,162	52,162	52,135	52,043	52,043	52,016
R-squared	0.001	0.084	0.085	0.004	0.086	0.087	0.001	0.095	0.095
Mean disease incidence	14.3%			10.3%			11.0%		
Impact of 1sd of forest loss 1 year ago as a percent of mean disease incidence	-7.67%	4.02%	3.95%	-9.65%	not st. sig	not st. sig	-5.08%	not st. sig	not st. sig