Deforestation, Malaria and Infant Mortality in Indonesia

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Abstract

Indonesia has experienced high levels of deforestation in recent years. In this paper, I investigate whether deforestation-induced malaria increases have led to higher infant mortality in the country. My empirical strategy exploits the pregnancy order-specific variation that exists in the risk of malaria—the disease is most likely to infect women during their first pregnancy and so adverse birth outcomes due to maternal malaria disproportionately affect firstborn children. I explore whether first born mortality changes differentially during deforestation relative to later born mortality. Results demonstrate that when mothers experience forest loss during pregnancy, firstborn children do indeed face a greater risk of infant mortality compared to other children. Apart from malaria, none of the factors that could change with declining forest cover (like air pollution) have such parity-specific effects. The findings thus point to malaria's role in the resulting deaths.

Keywords: deforestation, malaria, infant mortality, Indonesia, health, environment

JEL codes: I10, I18, J13, O13, Q23, Q57

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1. Introduction

The world's forests, being rich biodiversity reserves and carbon sinks, provide crucial ecosystem services. High rates of forest loss and degradation around the world are, however, increasingly threatening such amenities (Foley et al, 2005). Between 2000 and 2012 alone, as many as 2.3 million square kilometres of global forests have disappeared (Hansen et al, 2013).[1] One of the potential consequences of the major transformations that occur during deforestation is an increase in the prevalence of malaria (Patz et al, 2000; Pattanayak and Pfaff, 2009), a disease that is one of the top causes of death worldwide (Lozano et al, 2012).

Indonesia is an interesting setting for studying the link between deforestation and malaria. The country has the third largest tropical forest reserves in the world after Brazil and the Democratic Republic of Congo (ITTO and FAO, 2011). Its forests are, however, facing growing pressures from factors such as rampant illegal logging. In the early 2000s, Indonesia lost more than 5,000 square kilometres of forests every year and in subsequent years, it experienced the greatest increase in forest loss in the world. By 2008, the last year of the time period covered by the current analysis, deforestation in Indonesia annually claimed almost 15,000 square kilometres of forests (Hansen et al, 2013). Two previous studies in Indonesia find reductions in forest cover levels to be correlated with higher malaria prevalence (Pattanayak et al, 2010; Garg, 2017).[2] However, it isn't clear whether the forest loss-induced spikes in malaria in the country are severe enough to bring about mortality, which is what I probe here with regard to a specific population group—infants.

Using data on forest cover levels in Indonesian districts between 2000 and 2008 from Burgess et al. (2012) and birth data from the Demographic and Health Surveys (DHS), I explore whether changes in infant mortality track forest cover changes within districts in a way that is consistent with a stylized fact established by the epidemiological literature on malaria.[3] While women in malaria-endemic settings are

[1] Global reforestation and afforestation efforts between 2000 and 2012 did, however, lead to the establishment of 0.8 million square kilometres of forests (Hansen et al, 2013).
[2] Pattanayak et al. (2010) find the negative link between forest cover and malaria to persist in undisturbed and intact forest regions.
[3] Indonesia's islands are divided into provinces and these are further sub-divided into districts.

especially vulnerable to infections during all their pregnancies, they are more susceptible during their first pregnancy. This pattern arises because the placenta that is created during the first pregnancy is a new organ with no immunity against the disease, but later pregnancies are protected to a greater extent by antibodies developed during malaria infections in previous pregnancies. Consequently, the poor birth outcomes (such as infant mortality) that are likely to arise due to maternal malaria infections are disproportionately concentrated among children born to women from their first pregnancies (Steketee et al, 2001; Guyatt and Snow, 2004; Nosten et al, 2004; Desai et al, 2007). Since there could be general differences in infant mortality probabilities for firstborn and later born children (Hobcraft et al, 1985; Mahy, 2003), I focus on comparing the change in infant mortality for firstborn children when their mothers face deforestation during pregnancy to the change for later born children. Apart from malaria, none of the other factors that move with declining forest cover (such as air pollution) are known to have parity-specific effects. In other words, if there is any change in infant mortality in the face of deforestation, this change will be the same for first and later born children unless women experience greater exposure to malaria during their pregnancies due to forest loss. Thus, if forest reductions during the pregnancy period are found to be more detrimental for the survival of firstborn children than other children, it will point to malaria's role in the resulting deaths. The identifying assumption of my empirical strategy is that except for malaria, district forest cover declines are uncorrelated with factors that differentially shape the mortality of firstborn and later born infants.

Using a district fixed effects approach, I find that firstborn infant mortality changes in a systematically different manner under deforestation than later born infant mortality. Specifically, when district forest cover falls by one standard deviation, firstborn children experience a one percentage point higher likelihood of dying than later born children. This account for almost one-third of the 3.7 percent of firstborn children in the study sample who die in infancy. I find that the increased firstborn mortality risks stemming from forest cover reductions during pregnancy are manifested in the neonatal period of infancy or the first 27 days of life (not the post-neonatal period or the remaining days in the first year of life), which is consistent with the tendency of infant deaths driven by prenatal conditions to occur soon after birth. While deforestation-induced malaria could lead to detrimental birth outcomes other than mortality (such as miscarriages), the evidence does not conclusively indicate that forest cover declines disproportionately promote foetal losses during women's first pregnancies. The dangers of reduced forest cover for firstborn children appear to be concentrated among the poor, rural residents, those who live in highly forested districts and male children. Finally, while Indonesia has different types of forests (for example, intact forests and degraded forests), the results suggest that deforestation in the intact (or primary) forests is driving increases in malaria prevalence.

I conduct several checks to establish the robustness of my findings. The results do not appear to emerge due to any systematic differences between first birth order children born amidst lower district forest cover and other children—the former's mothers do not have different characteristics, nor are they more likely to be deprived of healthcare services. The results persist when I measure forest cover variations within districts in different ways and when I employ alternative empirical models. Furthermore, when I restrict the sample to more recent births to limit potential misassignment of births to the forest cover of the wrong districts due to inter-district migration of mothers after births (the data I use do not have migration information), there is no qualitative change in my conclusion that firstborn children face a higher mortality risk during forest cover declines. I also discuss why migration trends within Indonesia might not be particularly worrisome for the validity of my results. Finally, the observed infant mortality-forest loss pattern holds when I estimate a model that is similar to the main empirical framework of my analysis but that has a finer level of fixed effects—those at the level of mothers.

This study is valuable for several reasons. First, it is vital to identify the short term and long term implications of the extensive environmental degradation that is taking place globally to underline the need to stem detrimental practices and to protect the groups that are most vulnerable. I focus on an immediate consequence of deforestation in Indonesia that is likely channelled through increases in malaria transmission during a period in which the country experienced the highest growth in forest loss in the world (Hansen et al, 2013).[4] Second, by investigating how deforestation during the in utero period shapes early life mortality, this research contributes to the body of literature on the manifold effects of

[4] This statistic pertains to the 2000-2012 period. The current study examines nine of these years—2000-2008.

health shocks suffered in the foetal period (Almond and Currie, 2011; Currie and Vogl, 2013). Third, while bolstering the empirical evidence on the link between forest loss and malaria incidence and the consequences of forest disappearance on human wellbeing, this analysis also adds to the growing literature that specifically focuses on implications for infant health (Pattanayak et al, 2010; Berazneva and Byker, 2017; Carrillo et al, 2018; Bauhoff and Busch, 2018). Finally, to my knowledge, this is the first study to probe the costs of malaria increases due to Indonesia's rapid rates of deforestation on a concrete population health indicator across all the forested islands in the country.

The rest of the paper is structured as follows. Section 2 discusses deforestation in Indonesia and the literatures relevant to this research. I describe the data and methods in Sections 3 and 4 respectively. Section 5 contains the results and Section 6 presents robustness checks. I conclude with a discussion in Section 7.

2. Background

2.1. Forest cover in Indonesia

Indonesia, a Southeast Asian country, has one of the largest stretches of tropical forests in the world. These forests are, however, facing rampant deforestation. Between 2000 and 2008, the forests felled in Indonesia would have covered an area of land that was double the size of the US state of Vermont (Burgess et al, 2012). While one of the most "megadiverse" countries (Mittermeier et al, 1997), Indonesia risks tremendous biodiversity declines due to its high rates of deforestation (Wilcove et al, 2013). Another consequence of forest loss is the release of large amounts of stored carbon and in fact, according to one estimate, Indonesia's carbon dioxide emissions are rivalled only by the United States and China (World Bank, 2007). Much of the logging in Indonesia has been driven by the expansion of industries such as oil palm, pulp and paper (Forest Watch Indonesia et al, 2002; Koh and Wilcove, 2008; Obidzinski and Dermawan, 2012). Deforestation has also received an impetus from the massive administrative decentralization of the country at the turn of the century—competition between the growing number of districts in wood markets has led to an increase in wood extraction (Burgess et al, 2012). Illegal logging likely accounts for 60 to 80 percent of all logging in Indonesia, forming a market worth one billion US dollars per year (CIFOR, 2004).

2.2. Malaria

Malaria, which is a major cause of mortality and morbidity in developing countries, shapes economic growth levels by impacting fertility, educational attainment and productivity (Sachs and Malaney, 2002; Barreca, 2010; Bleakley, 2010a; Cutler et al, 2010; Lucas, 2010; Barofsky et al, 2011; Chang et al, 2011; Lucas, 2013; Percoco, 2013; Mora-Garcia, 2018). In 2008, there were about 243 million cases of malaria globally and these resulted in 863,000 deaths (WHO, 2009). Malaria is particularly dangerous for children under the age of five; estimates suggest that a child dies every two minutes from the disease (WHO, 2016). Pregnant women also face large risks—malaria during pregnancy increases the likelihood of maternal anaemia and of poor birth outcomes.[5] The latter—intrauterine growth retardation, prematurity and/or low birth weight—could emerge, for instance, if immune responses to malaria infections require glucose and oxygen to be diverted from the foetus to the mother. These adverse outcomes, in turn, heighten the risk of infant mortality. Women are more vulnerable to malaria during their first pregnancy than during later pregnancies, that is, when they are primigravidae rather than multigravidae. The placenta, when it is created for the first time, is a new organ that has no immunity against the disease, and thus there is a high probability of it being infected. Later placentas are protected to a greater extent by the antibodies produced during exposure to malaria parasites in earlier pregnancies (Steketee et al, 2001; Guyatt and Snow, 2004; Nosten et al, 2004; Desai et al, 2007). Due to this kind of parity-specific variation in the risk of maternal malaria, firstborn children experience the brunt of the resulting adverse outcomes and are therefore expected to suffer more when there is an increase in malaria incidence. Conversely, firstborn children are likely to benefit disproportionately when malaria declines. This type of first child advantage was documented in the aftermath of a country-wide malaria

[5] The *Plasmodium falciparum* parasite causes most human malaria infections and it affects pregnant women more than non-pregnant women (Guyatt and Snow, 2004). In Indonesia, a malaria-endemic country, *P. falciparum* is responsible for the majority of malaria cases (Elyazar et al, 2011; WHO, 2016).

control program in Sri Lanka in the 1940s which effectively eliminated malaria—firstborn children experienced the largest improvement in the probability of surviving childhood (Lucas, 2013).

2.3. Deforestation and malaria

Forest cover losses could increase malaria incidence through different pathways. Deforested lands are often used for agriculture, and the irrigation ditches and canals that are set up for farming create new breeding sites for mosquito vectors. Temperature increases due to forest cover reductions also aid malaria transmission. Accumulated water on lands cleared of forests tends to have a neutral pH by virtue of being exposed to strong sunlight and this is favourable for the development of mosquito larvae. Another mechanism is the loss of biodiversity—the reduction or elimination of predators (such as dragonflies) leads to mosquito proliferation (Patz et al, 2000; Pattanayak and Pfaff, 2009).

There is evidence of a positive association between deforestation and malaria prevalence in Brazil (Olson et al, 2010; Terrazas et al, 2015), Paraguay (Wayant et al, 2010), Malaysia (Fornace et al, 2016) and Nigeria (Berazneva and Byker, 2017). An investigation across multiple malaria-endemic countries also finds similar results (Austin et al, 2017). Within the Indonesian context, Pattanayak and colleagues (2010) identify a negative link between undisturbed forest cover levels and child malaria in a region within Flores, one of the country's islands, and Garg (2017) finds that in forested districts, deforestation increases the probability of village-level malaria outbreaks. Among other research on the topic, one analysis in Brazil suggests that forest cover declines might actually decrease the malaria burden (Valle and Clark, 2013), though the conclusions of this study have subsequently been questioned (see Hahn et al (2014a) as well as the response from Valle (2014)), and a couple fail to find evidence of a relationship between forest loss and malaria incidence (Hahn et al (2014b) focus on Brazil and Bauhoff and Busch (2018) use a multi-country sample).

2.4. Other channels through which forest cover could shape human health

Forest cover levels could shape human health through channels other than malaria. Residents of densely forested areas could experience poor health outcomes since these regions are likely to be remote and have low levels of infrastructure development (Dewi et al, 2005). In Indonesia, the industries driving much of the deforestation (like timber and palm oil) are major sources of employment (Hunt, 2010), and so declining forest cover is expected to move in tandem with more jobs and income, and with improvements in nutritional status and health services. Forests are often cleared with slash and burn practices, which lead to forest fires; the resulting air pollution has been found to shape adult health status, birth outcomes, early-life mortality and child physical development (Frankenberg et al, 2005; Jayachandran, 2009; Carrillo et al, 2018; Rosales-Rueda and Triyana, 2018).

Since several of the mechanisms discussed above could operate at the same time, the net impact of forest cover loss on overall infant mortality is ambiguous and it is difficult to back out the contribution of any one of these channels from the total effect.[6] It is important to note, however, that none of the potential consequences of deforestation, except for malaria, are known to have parity-specific effects on infant mortality—higher levels of malaria (which tend to be correlated with forest cover declines) are more dangerous for children born out of women's first pregnancies. In the current analysis, I exploit this stylized fact to understand whether deforestation-induced increases in malaria lead to higher infant mortality in Indonesia.

3. Data

I use data from several sources for this analysis. I describe these data below.

3.1. Forest cover data

The forest cover information that I use is from a dataset compiled by Burgess and co-authors (2012) based on Moderate Resolution Imaging Spectroradiometer (MODIS) satellite images at a 250-meter by 250-meter resolution. The data indicate the total number of units of land that is forested in an Indonesian district in a certain year and it contains this information for each year between 2000 and 2008. Given that the Burgess et al. 2012 dataset covers only the main forest islands of Indonesia—Sumatra,

[6] Though several of the aforementioned studies on deforestation-induced air pollution have used the geographical and/or time variation in exposure to forest fires to identify the plausibly causal impacts of forest fires on health outcomes (Frankenberg et al, 2005; Rosales-Rueda and Triyana, 2018; Jayachandran, 2009).

Figure 1: Forested islands of Indonesia

(color to be used online only)

Kalimantan, Sulawesi and Papua, I too focus on just these regions.[7] These islands are delineated in the map presented in Figure 1.

Based on the availability of birth data (which I describe below), I focus on 276 districts in Indonesia. These districts are richly forested—in 2000 (the first year in the study period), half of them have 83 percent or more of their total area covered in forests. However, between 2000 and 2008, almost 75,000 square kilometres of the country's forests disappear, with districts losing between 0.5 and 34 percent of initial forest cover (median district forest loss stood at three percent of 2000 forest levels) and none increasing their forest cover. Figure A1 in Appendix A depicts the percentage of initial district forest cover that disappeared during the study period. I arrange districts in ascending order of initial forest cover (measured in square kilometres) along the x-axis, such that the districts to the left have the least forest cover in 2000 and the ones to the right have the most. Note that there does not appear to be any clear systematic patterns between initial forest cover levels and forest loss.[8]

For this analysis, I capture forest cover variations within a district by constructing within district annual forest z-scores (akin to Garg, 2017 who also uses the same forest data as I do) with the following formula:

$$\text{z-score}_{dt} = (\text{annual\_forest}_{dt} - \text{mean\_annual\_forest}_{d}) / \text{st\_dev\_annual\_forest}_{d} \qquad (1)$$

where $\text{annual\_forest}_{dt}$ is the total forest cover in district d in year t, $\text{mean\_annual\_forest}_{d}$ is the average yearly forest cover in district d between 2000 and 2008, and $\text{st\_dev\_annual\_forest}_{d}$ is the standard deviation of yearly forest cover in district d during this time period.

Essentially, z-score_{dt} relates the change in forest cover that took place in a district during a year to the average annual levels of forest cover within the district during the study period. Since the z-scores measure forest change *within* districts, a one standard deviation in study period yearly forest cover in one district represents a different level of forests than a one standard deviation in another district. When

[7] The other islands (such as Java, Bali, Nusa Tenggara Barat and Nusa Tenggara Timur) have little forest cover.
[8] The highest forest loss during the study period occur in Sumatra and Kalimantan. Districts in Papua, which have substantial forests, face the least amount of deforestation.

averaged across all districts, one standard deviation in annual forest cover between 2000 and 2008 is about 98 square kilometres.[9]

3.2. Birth data

The birth data that I use are from the Demographic and Health Surveys (DHS).[10] Each DHS is a nationally representative household survey that collects data on a wide range of population, health and nutrition indicators. The DHS interviews women between the ages of 15 and 49 and compiles information on their fertility history—the date of birth of all livebirths, the age at death of any children who died and the end dates of pregnancies that did not result in livebirths. Detailed data on prenatal care and health inputs are collected for children born in the five years before the survey. For this analysis, I use data from the DHS rounds that were conducted in Indonesia in 2002, 2007 and 2012. I stack the births from the study period recorded in these three surveys, and subsequently link each birth to the forest cover that prevailed in the presumed district of birth and a year between 2000 and 2008. Since the surveys did not record the district a child was born in, I assume that the district of residence of a woman at the time of the survey is the district in which she conceived and had all her children.[11] I do, however, later conduct a check for this assumption. The year of forest cover exposure that I use pertains to the year in which a child's mother spent her early or first six months of pregnancy (this corresponds to the early in utero period of the child).[12] I focus on this period since malaria in early pregnancy has been found to increase the severity of the adverse birth outcomes that are likely to arise due to maternal malaria (Kalilani et al, 2010; Huynh et al, 2011; Griffin et al, 2012; Rijken et al, 2012).[13]

Since the DHS birth data are based on retrospective accounts, the possibility of recall error (for example, with regard to the date of birth) might go up as the gap between birth and survey date increases. In

[9] The lowest and highest study period forest cover standard deviations are zero and 1,405 square kilometres respectively.
[10] The Indonesia Family Life Survey (IFLS) is another rich source of demographic data from the country, but I am unable to use it because its sample size is considerably smaller than that of the DHS and it doesn't survey across all the forested islands of Indonesia.
[11] I drop the births of women who were visitors to the households in which they were interviewed since the children of these women could have been born in different districts.
[12] When these months extend over two different calendar years, I use the year in which a women spent half or more of her early pregnancy.
[13] Studies examining this topic have defined early pregnancy in different ways—13 to 26 weeks of gestation (Kalilani et al, 2010), up to four months of gestation (Huynh et al, 2011), up to 20 weeks of gestation (Griffin et al, 2012) and the first half of pregnancy (Rijken et al, 2012).

addition, births that had taken place a long time before a DHS survey might have occurred amidst circumstances very different from those that exist during the time of the survey. For example, during an earlier birth, a woman might have lived in a different district or had a very different economic status. To limit bias from such issues, I include in the study sample only children born in the five years preceding each DHS.

The main outcome variable that I use is an indicator variable for infant mortality which captures whether a child died within his or her first year of life. Since this variable can be defined only for those children who have been fully exposed to the risk of death in infancy, I restrict the sample to children who had been born at least one year before their mothers were surveyed by the DHS. This leaves me with a main sample of 13,215 births from pregnancies occurring between 2000 and 2008 in 276 districts. Of these children, 469 or 3.55 percent died in infancy.[14]

I construct a number of other variables from the DHS data to control for factors that might shape a child's survival prospects—gender of the child, age of the mother at birth and its squared term, the mother's education (in years), whether the birth was a multiple birth, rural residence, wealth quintile and birth month.[15] Since maternal malaria's effects on children are expected to vary by parity, I create an indicator variable for the firstborn child with the birth order data. Table 1 summarizes these variables for the main sample of births.

[14] This figure is similar to national infant mortality statistics during the study period—infant deaths claimed 3.5 percent of all livebirths between 1998 and 2002, and 3.4 percent of those between 2003 and 2007 (Statistics Indonesia and ORC Macro, 2003; Statistics Indonesia and Macro International, 2008).

[15] The wealth quintile a household belongs to is identified with the wealth index calculated by DHS staff based on the assets owned by a household.

Table 1: Descriptive statistics for the main sample of live births

Variable	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
Gender - female	0.473	0.499	0	1
Age of mother at birth of child	27.076	6.244	12	48
Mother's education (in years)	8.272	4.034	0	18
Multiple birth	0.015	0.123	0	1
Rural residence	0.655	0.475	0	1
Wealth index	2.405	1.372	1	5
Birth month	7	3	1	12
First birth	0.319	0.466	0	1
Infant mortality	0.035	0.185	0	1
District-level characteristics during early pregnancy of women - annual measures				
Forest cover (in square kilometers)[a]	4,848	6,600	0	45,069
Total precipitation (in centimeters)[a]	215.785	69.479	17.260	502.860
Monthly mean temperature (in degree Celsius)[a]	25.546	3.014	11.408	29.025
Real GDP per capita (in IDR million)[b,c]	7.526	13.154	0.604	270.801
Observations	13,215			

Notes: Sample includes children born 1-5 years before the DHS surveys.
[a]These variables are converted to within district z-scores for the empirical analysis.
[b]Logged for subsequent analysis.
[c]IDR refers to Indonesian Rupiah. These are in 2000 prices and include production in the oil and gas sector.

3.3. Other data

Since circumstances during early life tend to strongly impact infant health and survival (Almond and Currie, 2011; Currie and Vogl, 2013), I obtain additional data to capture environmental and macroeconomic conditions in Indonesian districts for the years in the study period. As with the forest cover measure, I match each child to the annual district-level conditions that prevailed during his or her in utero period.

I pull monthly precipitation (totals) and air temperature (means) from time series data available from the University of Delaware (Matsuura and Willmott, 2009). I identify the weather station that is closest to each district (by using the latitude and longitude of the center of the district) and use the matched station’s measurements to construct within district annual precipitation and temperature z-scores (using a formula similar to (1)).

I also use logged annual per capita district-level gross domestic product (GDP) in constant prices to account for changing economic conditions over time. To create this variable, I obtain annual real GDP (in million Indonesian Rupiah or IDR with 2000 being the base year) and population figures for each of the study years from the World Bank's Indonesia Database for Policy and Economic Research (INDO-DAPOER).[16] These variables are also summarized in Table 1.

4. Methods

One could estimate the relationship between forest cover and infant deaths by comparing the level of mortality in highly forested districts with that in less forested districts. However, given that these districts are likely to be very different from one another, the results would be biased. I thus use a fixed effects approach to examine how the relationship between forest cover and infant mortality changes over time *within districts*.

As discussed above, firstborn children and later born children face very different risks when their mothers are exposed to malaria during pregnancy. Note that since first births tend to be riskier than later births (Hobcraft et al, 1985; Mahy, 2003), these two groups could have different mortality probabilities in general.[17] However, irrespective of these differences, all factors that change concurrently with forest cover, *except for malaria*, should impact firstborn and later born infants in the same way. For instance, air pollution from the fires used to clear forests is as dangerous for firstborn children as it is for other children. I can thus use later born children as a control group to approximate how firstborn infants would fare under deforestation if it wasn't accompanied with increases in malaria. My empirical strategy is to compare the change in infant mortality for firstborn children when districts experience deforestation to the change experienced by later born children. The identifying assumption is that apart from malaria prevalence rates, district forest cover variations are uncorrelated with factors that shape the mortality of firstborn infants differently than the mortality of later born infants. It is important to

[16] The INDO-DAPOER data are available at https://data.worldbank.org/data-catalog/indonesia-database-for-policy-and-economic-research. I use GDP including oil and gas, but the study results remain unchanged when I use GDP excluding oil and gas.

[17] Women undergo permanent anatomical changes when pregnant for the first time and these facilitate foetal development during later pregnancies to a greater degree than was possible during the first pregnancy. This leads to better outcomes during later births (Khong et al, 2003).

highlight here that my approach will underestimate the total infant mortality costs due to the malaria increases brought about by deforestation since it will not capture the costs for later born children, which while lower than that of firstborn children, will not be zero.

I use the following estimation model for my analysis (similar to the one used by Garg, 2017):

$$M_{idt} = \alpha_1 * Forest\_Cover_{dt} + \alpha_2 * First_{idt} + \alpha_3 * Forest\_Cover_{dt} * First_{idt} + \alpha_4 * X_{idt} + \alpha_5 * Z_{dt} + \mu_d + \eta_{lt} + \alpha_5 Y_p + \varepsilon_{idt} \quad (2)$$

where M_{idt} is the infant mortality variable for child i whose early in utero period was spent in year t in district d, $Forest\_Cover_{dt}$ is the forest cover measure for district d in year t, and $First_{idt}$ is an indicator variable that turns on if a child is a firstborn child. X_{idt} are the child-level control variables listed in the Data section. Z_{dt} is a vector of time varying control variables for district d in year t such as precipitation. μ_d are district-level fixed effects which account for time-invariant district heterogeneity (like geography, culture and institutional factors), η_{lt} are indicators for island l and year t which control for occurrences common to all districts within an island during the year, and Y_p represents a linear time trend which varies by province, thus allowing infant mortality in all districts in a province to experience a common linear trend. ε_{idt} is the error term pertaining to child i in district d and year t. I cluster the standard errors at the level of the district and estimate linear probability models (LPM) because of problems associated with the use of non-linear models with fixed effects (Greene, 2004; Karaca-Mandic, 2012). However, as part of the checks I conduct later, I test whether the results hold when using the logit and probit models.

α_3 is the coefficient of interest in (2). Since the goal is identify the implications of deforestation, one can multiply this coefficient with -1 to understand whether firstborn children fare differently than other children when district forest cover falls by one unit (that is, by one standard deviation). If the product is positively signed, it would show that forest loss in Indonesia imposes a greater risk for firstborn children than for other infants, thus highlighting that the increases in malaria due to deforestation are severe enough to bring about mortality in this group.

By estimating model (2), I am essentially examining how the first versus later born infant mortality gap tracks forest cover changes within districts net of child-level characteristics, several district-level time-varying variables, island wide yearly changes and province-specific linear time trends. It is possible that there are time-varying district features that I fail to account for in the specification and that are associated with forest cover and with predictors of infant mortality. Note though that these would be problematic only if they differentially influence first child mortality. Later I conduct several robustness checks to gauge the sensitivity of the results that I obtain with my main empirical specification.

5. Results

5.1. The implications of forest cover change for infant mortality

I present the main findings of my analysis in Table 2. The first column contains the results obtained by estimating a sparse version of model (2) and subsequent columns include additional sets of controls.[18] The coefficients on the forest variable show that forest cover declines (and the concomitant changes in infrastructure, industrial activity, employment patterns, pollution and disease ecology) are associated with a decrease in mortality among later born infants. However, the relationship is only marginally significant in column 5 which contains the full set of controls.[19] The coefficients on the firstborn variable are positively signed, which is expected given existing evidence on the higher risks for poor birth outcomes during first births (Hobcraft et al, 1985; Mahy, 2003). Note though that these coefficients are not statistically significant indicating that the general mortality likelihood of first and later born infants in Indonesia during the study period is essentially the same.

[18] Table A1 in Appendix A presents additional covariate coefficients from the fullest specification.

[19] If I were to estimate a model which only included this forest cover variable (in other words, if the forest cover-firstborn interaction term was omitted), its coefficient would capture the overall relationship between forest cover and mortality for all infants. The results of such a specification indicate that all infant mortality goes down with deforestation but the coefficient is statistically indistinguishable from zero. These results are available upon request.

Table 2: Forest cover and infant mortality

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Infant mortality				
Forest cover	0.004*	0.005	0.004	0.009*	0.009*
	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)
First birth	0.001	0.002	0.002	0.002	0.002
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
Forest cover*First birth	-0.011***	-0.012***	-0.012***	-0.012***	-0.012***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
District-level fixed effects	X	X	X	X	X
Child-level controls, DHS survey indicators		X	X	X	X
District time-varying controls (precipitation and temperature z-scores, log real GDP per capita)			X	X	X
Island-year indicators				X	X
Province-level linear time trends					X
Observations	13,215	13,215	13,215	13,215	13,215
R-squared	0.026	0.042	0.043	0.045	0.046

Robust standard errors (clustered at the district-level) in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Forest cover during the year in which a woman spent her early pregnancy is measured as within district z-scores. Child-level control variables include gender of the child, age of the mother at birth and its squared term, mother's education, and indicators for multiple birth, rural residence, wealth index and birth month. Sample includes children born 1-5 years before the DHS surveys. Mean infant mortality for all children and first born children are 0.035 and 0.037 respectively.

In interpreting the variable of interest, the interaction term between forest cover and the firstborn indicator, I multiply the coefficients with -1 to identify the consequences of forest loss. Relative to other infants, firstborn infants do indeed face a greater risk of death when their mothers experience forest cover declines early in their pregnancy. This relationship is robust to the inclusion of different controls and is statistically significant at the one percent level. The likelihood of death for a firstborn infant versus a later born infant increases by about one percentage point when forest cover falls by one standard deviation within a district.[20] Since 3.7 percent of firstborn children in my sample die in infancy, the point estimate on the variable of interest represents almost one third of all firstborn deaths. Research in the public health literature suggest that three to thirty percent of all infant deaths in malaria-endemic

[20] Note that the magnitude of the forest coefficient for firstborn children is larger and opposite in sign to the forest coefficient for later born children. This indicates that all the malaria and non-malaria factors that move with deforestation bring about a net increase in firstborn infant mortality.

regions could be due to the disease (Lucas, 2013). Since I am likely capturing only a portion of malaria-induced mortality among firstborn children in Indonesia, that which is due to deforestation, malaria deaths among this subset of infants in the country could be higher than the range expected based on these prior studies.

5.2. Mortality at different phases of infancy and foetal loss

A child's infancy consists of two phases—the first 27 days of life are referred to as the neonatal period and the rest of a child's first year of life is called the post-neonatal period. Infants are most vulnerable during the former phase (Lawn et al, 2005) and in fact 269 of the 469 infant deaths in the study sample (57 percent) occur during this period.[21] Neonatal deaths are more likely to arise due to circumstances prevailing during the prenatal phase and during the time of birth, while post-neonatal deaths are shaped to a greater extent by environmental conditions after the birth of a child (Rowley et al, 1994). Since the parity-specific variation in health outcomes that I exploit stems from exposure of mothers to malaria during pregnancy (that is, during the prenatal period), we would expect the heightened risks for firstborn children due to forest loss to be concentrated in the period soon after birth than in the later part of infancy.[22] In this section, I examine whether this is indeed the case.

In Table 3, I look at the parity-specific implications of forest cover separately for the neonatal and post-neonatal periods (columns 1 and 2 respectively). I find that forest cover reductions increase the mortality risks faced by firstborn children relative to those born later in the neonatal period (a 0.9 percentage point decline), but not in the post-neonatal period (while the coefficient is negatively signed, it is statistically indistinguishable from zero).[23] The time at which the observed parity-specific mortality patterns are manifested strengthens the argument that the results stem from women's exposure to malaria during pregnancy.

[21] In all of Indonesia, 57 (56) percent of infant deaths during the 1998-2002 (2003-2007) period occurred during the neonatal phase (Statistics Indonesia and ORC Macro, 2003; Statistics Indonesia and Macro International, 2008).
[22] Recall that each child is linked to the district forest cover that prevailed during his or her mother's pregnancy. This measure thus captures the potential level of malaria incidence during the prenatal phase.
[23] The post-neonatal mortality sample is smaller than the neonatal mortality sample, since it excludes infants who have died in the neonatal period.

Table 3: Forest cover and its relationship with mortality at different phases of infancy and foetal loss

	(1)	(2)	(3)
Dependent variable:	Neonatal mortality	Post-neonatal mortality	Foetal loss
Forest cover	0.008**	0.001	0.004
	(0.004)	(0.004)	(0.009)
First birth/pregnancy	0.002	0.000	0.000
	(0.004)	(0.003)	(0.006)
Forest cover*First birth/pregnancy	-0.009***	-0.003	-0.004
	(0.003)	(0.002)	(0.005)
Observations	13,215	12,946	14040
R-squared	0.042	0.038	0.104
Mean of dependent variable - all children	0.02	0.015	0.069
Mean of dependent variable - first born children	0.023	0.015	0.061

Robust standard errors (clustered at the district-level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Forest cover during the year in which a woman spent her early pregnancy is measured as within district z-scores. The district fixed effects models presented in columns 1-3 include the following child-level controls: gender of the child, age of the mother at birth and its squared term, mother's education, and indicators for multiple birth, rural residence, wealth index and birth month. Other controls are island-year indicators, province-level linear time trends, DHS survey indicators, district-level precipitation and temperature z-scores, and per capita log real GDP. The models in columns 4 and 5 do not include gender, multiple birth and birth month controls. Sample includes births/foetal losses that took place 1-5 years before the DHS surveys.

It is important to point out that infant mortality is not the only poor birth outcome that could arise due to maternal malaria. Infected women also face higher risks for miscarriages and stillbirths (Guyatt and Snow, 2004; Nosten et al, 2004; Desai et al, 2007). Thus, concentrating on only live births could understate the potential early life malaria risks brought about by deforestation in Indonesia. Additionally, while I use birth order to identify firstborn children for the main analysis, birth order would not be equal to pregnancy order if a woman suffered foetal losses and since the risk of malaria infections varies across pregnancies, the latter would be the more relevant variable to use. Thus, I now focus on the outcome of foetal loss and employ women's pregnancy ordering to investigate if there are differential implications of forest loss by pregnancy.

The DHS surveys asked women if they "ever had a pregnancy that miscarried, was aborted, or ended in a stillbirth" and if so, the date when the pregnancy ended (Statistics Indonesia and Macro

International, 2008). This information was collected for up to two terminated pregnancies per respondent. I add these pregnancies to the birth data and construct a pregnancy ordering for each woman.[24] In the resulting pregnancy-level sample, each observation corresponds to a pregnancy, some of which led to live births (the 13,215 births included in the main sample) but some of which did not.[25] In other words, the pregnancy-level sample is a larger sample comprising of 14,040 observations. Unfortunately, it is not possible to identify which of the foetal losses were due to abortion and so I include all reported losses in this part of the analysis. 962 or about seven percent of pregnancies did not lead to a live birth. I create a foetal loss indicator variable that turns on for these pregnancies.

I probe the foetal loss outcome with model (2) in the last column of Table 3. For pregnancies that did not lead to live births, information such as gender of the child and whether it was a multiple pregnancy is not available, and so the specification for this outcome has a smaller set of control variables.[26] The coefficient of interest does not attain statistical significant but its sign indicates that forest declines might be more likely to bring about pregnancy losses when a woman is pregnant for the first time versus when a woman is pregnant with a higher order child. Note that foetal loss is likely to be measured with error due to recall issues (Beckett et al, 2001), thus leading to a situation with error in the dependent variable.[27] The resulting reduction in power could be responsible for the imprecise estimate that I obtain. Nevertheless, it is unclear from the results whether foetuses during women's first pregnancies are disproportionately endangered by deforestation.

5.3. Sub-group analysis

[24] The pregnancy order of some observations is not equal to their birth order—this occurs for pregnancies that do not lead to births and thus do not have birth orders, and for children whose pregnancy order is higher than their birth order because one of their mother's earlier pregnancies that ended in foetal loss is now being accounted for. Some women were unable to report the year in which they lost pregnancies which makes it difficult to construct an accurate ordering of their pregnancies. I drop all the pregnancies and births reported by these women when examining foetal loss.
[25] Since the main outcome variable of infant mortality is defined only for births that took place one to five years before the surveys, I keep only those study period pregnancies that ended or led to a birth one to five years prior to each DHS.
[26] While women were asked about both the month and year in which their pregnancies ended, there is a lot of missing data on the former and so I do not include month as a control variable when exploring foetal loss. Age of mother at birth is replaced with age of the mother when the pregnancy ended.
[27] A pregnancy that did not lead to a live birth might be less salient than one which did lead to a live birth, and might thus be more likely to be forgotten.

I examine whether there is heterogeneity in deforestation's consequences for infant mortality across sub-groups defined by wealth status (poor or non-poor), type of place of residence (rural versus urban), initial level of district forest cover (high or low) and gender. Forest cover changes could be expected to have more of an impact on poorer and rural populations since they possibly live closer to forested areas and/or are more dependent on them for livelihoods or consumption purposes than their richer and urban counterparts. Furthermore, the influence of deforestation on malaria rates could differ in districts with varying levels of initial forest cover—it will presumably be stronger in areas with dense forests than in districts that had little or scattered forests to start with.[28] Finally, the results could also vary by gender since in utero shocks have been found to affect male foetuses more than female foetuses (Kraemer, 2000; Eriksson et al, 2010; Almond and Mazumder, 2011).[29]

In Table 4, I estimate model (2) separately for these different strata. As hypothesized, the results in the entire sample appear to be driven by the poorest (column 1), rural residents (column 3), high initial forest districts (column 5) and male infants (column 7). While the variable of interest in the other columns is negative, it is at most marginally significant.

[28] I split the study districts into high and low forest cover districts using median initial (2000) district forest cover.
[29] Male foetuses are more dependent on their mothers' current diets than female foetuses, for example, because they grow faster in the womb. They are, thus, more vulnerable to any nutritional deficiencies that occur during the prenatal period (Eriksson et al, 2010).

Table 4: Forest cover and infant mortality - heterogeneous effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: Infant mortality							
Sub-groups:	Poorest (Lowest two wealth quintiles)	Less poor (Upper three wealth quintiles)	Rural	Urban	High initial forest cover district	Low initial forest cover district	Boys	Girls
Forest cover	0.008	0.008	0.012	0.004	0.003	0.007	0.003	0.014*
	(0.008)	(0.007)	(0.009)	(0.005)	(0.014)	(0.005)	(0.008)	(0.008)
First birth	0.006	0.001	0.002	0.003	-0.005	0.008	0.003	0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)
Forest cover*First birth	-0.019***	-0.006	-0.015***	-0.008	-0.017***	-0.009*	-0.016**	-0.008*
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
Observations	7,662	5,553	8,657	4,558	6,492	6,723	6,959	6,256
R-squared	0.072	0.067	0.061	0.087	0.049	0.050	0.072	0.068
Mean of dependent variable - all children	0.041	0.028	0.040	0.027	0.039	0.032	0.039	0.031
Mean of dependent variable - first born children	0.044	0.029	0.042	0.029	0.042	0.033	0.045	0.029

Robust standard errors (clustered at the district-level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Forest cover during the year in which a woman spent her early pregnancy is measured as within district z-scores. The district fixed effects models include the following child-level controls: gender of the child, age of the mother at birth and its squared term, mother's education, and indicators for multiple birth, rural residence, wealth index and birth month (a control variable is omitted if it is used to define the sub-group being analyzed). Other controls are island-year indicators, province-level linear time trends, DHS survey indicators, district-level precipitation and temperature z-scores, and per capita log real GDP. Sample includes children born 1-5 years before the DHS surveys.

5.4. The malaria implications of deforestation in different types of forests

Indonesia's land surface is divided into different types of land-use zones and the Burgess et al. 2012 forest data that I use quantify a district's annual forest cover separately for these different zones. The areas that are denoted as conservation and protection zones contain primary or intact forests where logging is illegal. The secondary or degraded forests are found in the production and conversion zones, and include commercial forests such as oil palm and pulp plantations; in these areas some logging is permitted (Margono et al, 2014).[30]

Given that Indonesia's secondary forests are fragmented and logged to a much greater extent than the primary forests, the ecological makeup of these forests is very different and so the malaria consequences of deforestation could vary based on where the forest loss is occurring. To illustrate, primary forests have rich biodiversity and so forest loss could threaten species that prey on mosquito larvae (such as dragonflies), leading to spikes in mosquito populations. Secondary forests are unlikely to have this channel for mosquito control in the first place and so deforestation in these forests might not be accompanied with similar increases in malaria (Garg, 2017). Two previous studies in Indonesia indicate that the extent of primary forest cover is indeed negatively correlated with malaria incidence but the results diverge for secondary forest cover—Pattanayak et al. (2010) detect a positive association between secondary forest cover levels and child malaria, whereas Garg (2017) finds no evidence of a relationship between the two variables. As a result, while it can be hypothesized that the disproportionate mortality burden imposed on firstborn infants due to maternal malaria exposure will emerge when forest loss occurs in primary forest regions, it is unclear whether the same pattern will arise within the context of deforestation in secondary forests. Here I explore the infant mortality implications of forest loss in the different types of forests in Indonesia.

Among the districts included in my study sample, 80 percent have both primary and secondary forests. The median proportion of initial district forest cover that was made up of primary forests was 29 percent (the maximum was 89 percent). Median secondary forest share within districts in 2000 was 26 percent

[30] There is a fifth types of land-use zone in Indonesia which is designated as the 'Other' category.

(with the maximum being 100 percent).[31] To identify the type of forest cover that matters, I estimate a version of model (2) in which I include the different types of forest cover as explanatory variables (primary, secondary, and both primary and secondary) along with their interactions with the firstborn variable. Table 5 indicates that when all these forest cover types are considered, only deforestation in primary forests contributes to higher first child mortality risks. Changes in secondary forest cover or concurrent changes in both types of forest cover do not seem to significantly shape the first versus later child mortality differential.

The differing malaria consequences of primary and secondary forest cover in Indonesia suggest that the forest cover-malaria relationship in Indonesia follows a pattern similar to the one observed in the Brazilian Amazon. Research in this context has shown increases in the rates of malaria during the early stages of ecosystem transformation, likely due to a rapid growth in larval habitats, but malaria transmission has stabilized and fallen with the continuation of forest clearing activities (de Castro et al, 2006).

[31] During the study period, median primary forest loss within districts stood at one percent of initial primary forest cover. The analogous figure for secondary forests was higher at three percent.

Table 5: Different types of forest cover and infant mortality

Dependent variable:	Infant mortality
First birth	-0.002
	(0.007)
Primary forest cover	0.018**
	(0.008)
Primary forest cover*First birth	-0.026**
	(0.011)
Secondary forest cover	-0.010
	(0.007)
Secondary forest cover*First birth	0.009
	(0.010)
Primary forest cover*Secondary forest cover	0.002
	(0.005)
Primary forest cover*Secondary forest cover*First birth	0.005
	(0.005)
Observations	10,070
R-squared	0.047

Robust standard errors (clustered at the district-level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Forest cover during the year in which a woman spent her early pregnancy is measured as within district z-scores. The district fixed effects models include the following child-level controls: gender of the child, age of the mother at birth and its squared term, mother's education, and indicators for multiple birth, rural residence, wealth index and birth month. Other controls are island-year indicators, province-level linear time trends, DHS survey indicators, district-level precipitation and temperature z-scores, and per capita log real GDP. Sample includes children born 1-5 years before the DHS surveys.

6. Robustness checks

In this section, I demonstrate that the main infant mortality results hold up against several checks.

6.1. Concurrent changes in maternal characteristics and healthcare services

Of all the potential consequences of deforestation, only malaria is known to have the parity-specific implications that I find evidence for in my analysis. To convincingly argue that my results stem solely from forest loss-induced spikes in malaria transmission, I would need to demonstrate that other factors that move concurrently with forest cover changes within Indonesian districts do not shape firstborn and later born infants differently.

As a first check, I investigate whether women giving birth to their first child in times of lower forest cover are systematically different from the women giving birth to the other children in my sample. If so, the results I see might be due to compositional changes and not due to declining forest cover. In Panel A of Table 6, I estimate equation (2) with various maternal features as outcomes. Columns 1-5 look at wealth groups and column 6 examines education. For my main specification, I would ideally have controlled for religious and ethnic characteristics. I am unable to do so, however, because the Indonesian DHS data that I use do not contain any information on ethnicity and religion was collected in only two of the three surveys (it was omitted from DHS 2012, which contributes more than 30 percent of my main sample). Here, I use what information is available on religion to probe whether variations in religious group affiliation track the variable of interest (columns 7-10). The results demonstrates that women who give birth to their first child in times of low district forest cover are not different on nine of the ten characteristics that I test for. It does appear, however, that the richest women are significantly more likely to have a firstborn child amidst declining district forest cover. Note though that wealth index is controlled for in all the empirical models I use in my investigations. Also, given that the richest women are likely to have higher nutritional status and healthcare access than other women, they could be expected to experience better birth outcomes. Thus the higher likelihood of first births among the richest during deforestation should actually work against finding greater forest loss-induced mortality risks for firstborn children.

Table 6: Maternal characteristics and concurrent health services

Panel A: Selection on observable characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:	Poorest wealth index	Poorer wealth index	Middle wealth index	Richer wealth index	Richest wealth index	Mother's education (in years)	Muslim	Protestant	Catholic	Hindu
Forest cover*First birth	-0.004	0.011	-0.002	0.010	-0.016**	0.090	-0.008	0.003	-0.005	0.005
	(0.008)	(0.008)	(0.007)	(0.008)	(0.006)	(0.072)	(0.010)	(0.009)	(0.004)	(0.003)
Observations	13,215	13,215	13,215	13,215	13,215	13,215	9,094	9,094	9,094	9,094

Panel B: Concurrent changes in health services

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	One or more antenatal care visits[a]	Received antenatal care in the first trimester[a]	Received iron supplement[a]	Had tetanus injection[a]	Delivery at a health facility[b]	Had first polio vaccine by age one[c]
Forest cover*First birth	0.002	0.008	0.008	0.005	-0.001	-0.005
	(0.005)	(0.011)	(0.011)	(0.009)	(0.008)	(0.009)
Observations	10,126	10,200	10,017	9,935	13,143	5,434

Robust standard errors (clustered at the district-level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Forest cover during the year in which a woman spent her early pregnancy is measured as within district z-scores. The district fixed effects models include the following child-level controls: gender of the child, age of the mother at birth and its squared term, mother's education, and indicators for multiple birth, rural residence, wealth index and birth month. Other controls are island-year indicators, province-level linear time trends, DHS survey indicators, district-level precipitation and temperature z-scores, and per capita log real GDP. During the years in which the DHS collected religion information, 99 percent of the children's mothers belonged to the four religious groups I examine in columns 7-10 in Panel A. Sample includes children born 1-5 years before the DHS surveys.

[a]These variables are available for the last birth of each woman in the five years before the survey.

[b]This indicator is available for all births in the five years before the survey.

[c]This was collected only by DHS 2002 and DHS 2007 for all surviving children born in the five years preceding the surveys.

I next explore whether firstborn children experiencing forest cover loss appear to be less likely to benefit from the health care services that promote infant survival, a trend that might be responsible for the first child disadvantages occurring during forest cover declines within districts. In Panel B of Table 6, I estimate equation (2) for several such outcomes (pulled from the DHS data)—receipt of antenatal care by mothers, antenatal care in the first trimester of pregnancy, receipt of iron supplementation during pregnancy, obtaining a tetanus injection while pregnant, delivery at a health facility and child polio vaccination by age one. Results show that first children born after forest cover loss do not have systematically different utilization rates for any of these services. This strengthens the argument that the observed first child disadvantages are stemming from forest cover reductions and not from other factors.

6.2. Sensitivity to the type of forest cover measure and model used

While I capture forest cover variation with within district z-scores for my main analysis, I gauge the sensitivity of the results to alternative measures of forest change in districts. I use variables akin to those that have been used in the literature exploring the consequences of rainfall shocks. I present these estimates in Table 7. The log deviation measure in column 1 captures the difference in the natural logarithm of the annual forest cover experienced by a mother during her early pregnancy and the natural logarithm of mean annual forest cover in her district over the study period (2000 to 2008) (this is the type of explanatory variable used in Rocha and Soares, 2015). Column 2 uses an indicator variable for very low forest cover within districts. This is coded one when forest cover during a woman's pregnancy lies more than one standard deviation below the average annual district forest cover between 2000 and 2008 (also used in Rocha and Soares, 2015). In column 3, I create a variable that is equal to one if forest cover in a district during a particular year is more than the 80th percentile of the distribution of annual forest cover in the district during the study period, negative one if it is less than the 20th percentile and zero if it is in between (as in Jayachandran, 2006 and Shah and Steinberg, 2017). Finally, column 4 uses total forest units in a district in a year.[32]

[32] Appendix B lays out the formulae for all these alternative forest cover measures.

Table 7: Employing different forest cover measures and other types of models

	(1)	(2)	(3)	(4)	(5)	(6)
Model:	Linear probability model				Logit[a]	Probit[a]
Forest cover measure used:	Log deviation	More than one standard deviation below district mean	80th & 20th percentiles	Level	Z-score	Z-score
Forest cover*First birth	-0.188**	0.014	-0.030***	-0.000	-0.014***	-0.015***
	(0.083)	(0.008)	(0.007)	(0.000)	(0.005)	(0.005)
Observations	13,215					

Robust standard errors (clustered at the district-level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Forest cover refers to the forest levels that prevailed in a district during the year in which a woman spent her early pregnancy. The district fixed effects models include the following child-level controls: gender of the child, age of the mother at birth and its squared term, mother's education, and indicators for multiple birth, rural residence, wealth index and birth month. Other controls are island-year indicators, province-level linear time trends, DHS survey indicators, district-level precipitation and temperature z-scores, and per capita log real GDP. Sample includes children born 1-5 years before the DHS surveys. Mean infant mortality for all children and first born children are 0.035 and 0.037 respectively. [a]The reported estimates capture the difference between the marginal effect of forest cover change on the mortality of firstborn infants and the marginal effect on later born infants.

Looking at the variable that identifies the implications of varying forest cover specifically for firstborn children, I find that while a change in the absolute levels of forest cover do not seem to matter (the coefficient in column 4 is essentially zero and statistically insignificant), a change in district forest cover that is sizeable given mean forest levels does make a difference. The coefficient of interest in column 2 is just outside the range of significance (its p-value is 0.107) but it is signed in the expected direction, implying that forest cover declines within a district are associated with an increase in the risk of mortality faced by firstborn children relative to other children.

Recall that I use LPM for the main analysis. In the last two columns of Table 7, I estimate equation (2) for the main outcome of infant mortality with the following nonlinear models—logit and probit. The difference between the marginal effect of forest cover change on firstborn mortality and the marginal effect on later born mortality is statistically significant and signed as in the main specification.

6.3. Dealing with migration concerns

In assigning district forest cover measures to births, I assume that the district a female respondent lives in at the time of a DHS is the district she lived in during all her pregnancies. Unfortunately, the DHS in Indonesia (at least for the surveys I use) did not collect information about respondents' migration history and so it is possible that I link some births to the forest cover of districts to which mothers moved after a pregnancy or birth. To gauge whether my results are driven by any potential inaccurate assignment of forest cover, I now focus on more recent births (those that took place two to four years before the survey in which they were recorded instead of the five year limit that I use in the main analysis), since these are more likely to have occurred in the districts women lived in at the time of the survey.[33]

The estimates for recent births are presented in Table 8. The coefficient on the forest cover variable for the first child is negatively signed throughout (indicating that forest loss is more dangerous for these children than for other children), but the coefficient loses significance in the last column. Note, however, that the sample size has fallen substantially, which could have led to low power.

While exploring migration-related factors that might affect the study findings, it is important to understand whether there are systematic reasons due to which women in Indonesia tend to give birth in districts other than their district of residence. This would occur, for example, if it was common for women in Indonesia to marry men outside their districts and to subsequently move to the husbands' districts post marriage, but to travel back to live in their natal homes during their pregnancy. Due to the ethnic diversity that prevails in Indonesia, not all communities practice virilocality, a practice under which women move to the residence of their husbands after marriage—for example, some ethnic groups are ambilocal, that is, the married couple resides with either the woman or the man's parents, and in fact, some groups are uxorilocal and couples live with the woman's family (Levine and Kevane, 2003). This variation makes it improbable that there would be a universal trend of pregnancy-related migration in Indonesia.

[33] Infant mortality is defined only for births that took place at least a year before they are recorded since at least a year has to pass after the birth of a child to observe whether a child survives his or her infancy. I am thus unable to examine infant mortality for births occurring in the year prior to the survey.

Table 8: Examining recent births

	(1)	(2)	(3)
	Dependent variable: Infant mortality		
Sample includes children born the following number of years before the DHS surveys:	4 years	3 years	2 years
Forest cover*First birth	-0.013***	-0.017**	-0.011
	(0.004)	(0.007)	(0.010)
Observations	9,926	6,286	3,549

Robust standard errors (clustered at the district-level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Forest cover during the year in which a woman spent her early pregnancy is measured as within district z-scores. The district fixed effects models include the following child-level controls: gender of the child, age of the mother at birth and its squared term, mother's education, and indicators for multiple birth, rural residence, wealth index and birth month. Other controls are island-year indicators, province-level linear time trends, DHS survey indicators, district-level precipitation and temperature z-scores, and per capita log real GDP.

Could other types of inter-district migration (for example, economic migration) in Indonesia affect the results of this analysis? Due to the following factors, I argue that overall migration patterns are unlikely to be a major concern. First, Jakarta, an important economic and political center in Java, tends to be the destination for much of the internal migration in Indonesia (Van Lottum and Marks, 2012), but it is excluded from my study sample since it is not located in one of the forested islands of Indonesia. As a result, migrants who were interviewed in Jakarta but had their children elsewhere would not show up in my sample.[34] Second, most migration within Indonesia is characterized by movement from rural areas to urban areas (Lu, 2010), and so even if my urban sample includes some children who were born in districts other than the districts in which their mothers were interviewed by the DHS, the rural sample will be less affected by such potential misassignments. Since the sub-group analysis I conduct suggests that the observed increase in firstborn mortality risks amidst deforestation is concentrated among the

[34] Indonesia did have a Transmigration program that began in the early twentieth century under the Dutch colonial rulers aimed at easing population pressures in the densely populated islands of Java and Bali (among other objectives). The program resettled individuals from these islands to the less populated "outer" islands. The forested areas I focus on are part of the latter group of islands and so migration under this program would have been problematic for my analysis. However, Indonesia's Transmigration scheme collapsed in the aftermath of the Asian financial crisis of 1997—before the beginning of my study period (Van Lottum and Marks, 2012; Bazzi et al, 2016).

rural sub-sample (column 3 in Table 4), any inaccurate assignment of forest cover to births due to my inability to observe migration patterns is not likely to be driving the study estimates.

6.4. Using a maternal fixed effects approach

As a final test, I estimate a model that is similar to equation (2) but that has a finer level of fixed effects—maternal fixed effects. In other words, I control for time-invariant heterogeneity at the level of mothers and essentially explore whether the mortality differential between a woman's firstborn and later born children varies with forest cover changes.

For the maternal fixed effects sample, I identify women who meet two conditions—those who had a first birth/pregnancy during the study years (2000-2008) and had two or more births/pregnancies during this time span. To make sure I have sufficient sample size, I do not restrict births/pregnancies to only those that took place in the five years before a DHS as I do in the main sample.[35] I do not use the maternal fixed effects framework as my main estimation approach because of the recall bias issues that arise when using information on births/pregnancies that took place a long time ago and because in the absence of migration information, using more recent births/pregnancies is one way in which I can increase the chances of accurately linking these to the districts in which they had taken place. Notwithstanding these limitations with the maternal fixed effects approach, it is useful to check whether the sign and significance of the coefficient of interest from the district fixed effects model hold when using this alternative model.

[35] In the maternal fixed effects sample, the maximum gap between a birth and the survey date would be 12 years if a birth took place in 2000 and it was recorded in the 2012 DHS.

Table 9: Results from maternal fixed effects models

	(1)	(2)	(3)	(4)
Dependent variable:	Infant mortality	Neonatal mortality	Post-neonatal mortality	Foetal loss
Total forest cover	0.014	0.025**	-0.012	0.031
	(0.014)	(0.012)	(0.009)	(0.021)
First birth	0.076***	0.053***	0.027***	0.202***
	(0.013)	(0.010)	(0.009)	(0.017)
Forest cover*First birth/pregnancy	-0.016	-0.031**	0.017	-0.050**
	(0.018)	(0.014)	(0.012)	(0.021)
Observations	6,667	6,667	6,439	7,681
R-squared	0.042	0.038	0.028	0.071
Number of mothers	2,992	2,992	2,984	3,361
Mean of dependent variable - all children	0.057	0.034	0.023	0.099
Mean of dependent variable - first born children	0.077	0.047	0.031	0.140

Robust standard errors (clustered at the district-level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Forest cover during the year in which a woman spent her early pregnancy is measured as within district z-scores. The district fixed effects models for columns 1-3 include the following child-level controls: gender of the child, age of the mother at birth and its squared term, indicator variables for multiple birth and birth month. Other controls are island-year indicators, province-level linear time trends, DHS survey indicators, district-level precipitation and temperature z-scores, and per capita log real GDP. Column 4 includes all these controls except for child gender, multiple birth and birth month. Sample includes births to women who had their first birth during the study period (2000-2008) and had more than one birth in these years.

I present results from the maternal fixed effects specification in Table 9. There are 2,992 (3,361) women who meet the criteria for inclusion in the birth-level (pregnancy-level) sample, and they have had between two and six births (the same range of pregnancies) during the study period. The coefficient on the interaction term between forest cover and the first birth indicator when examining infant mortality (column 1) is signed as expected, but it doesn't attain statistical significance. However, as in the main sample, a decline in forest cover significantly increases the mortality risks experienced by firstborn children relative to other children in the neonatal period of infancy (column 2), but not in the post-neonatal period (column 3). The last column shows that deforestation disproportionately endangers foetuses during women's first pregnancy—this is qualitatively similar to what I find in the main sample. Overall, Table 9 point to the robustness of the district fixed effects estimates. Recall, however, that due to the two conditions used to identify women for the maternal fixed effects specification, this sample is smaller than the sample of all women giving birth in the forested districts of Indonesia during the study period. The two samples appear to be systematically different—for example, the comparisons in Table A2 in Appendix A show that the mothers in the maternal fixed effects sample have more education, are more likely to live in urban areas and are wealthier. Due to such differences, the magnitude of the estimates from the maternal fixed effects specification might not necessarily be widely generalizable.

7. Discussion and Conclusion

The evidence from this analysis demonstrates that in Indonesia between 2000 and 2008, firstborn children faced a greater risk of infant mortality compared to other children when exposed to deforestation in utero. Of the various potential consequences of forest cover decline, only malaria is known to have such parity-specific effects. I find that when forest cover fell by one standard deviation within districts, the likelihood of death for a firstborn infant relative to a later born infant increased by one percentage point.

To provide a sense of what the point estimate capturing the consequences of forest decline for firstborn children translates into in terms of actual infant deaths, I conduct some back of the envelope calculations. The DHS 2007 country report contains several of the indicators I need for this estimation and so I perform this exercise for the year 2007. The crude birth rate in Indonesia was 20.9 per 1,000 individuals. Given that the 2007 population in the study districts was about 77.4 million (this population data is from the World Bank DAPOER dataset), the birth rate implies that there were roughly 1.6 million births in these districts. Now in order to identify how many of these births were likely to have been first births, I divide the number with Indonesia's total fertility rate (2.6 births per woman) to reach an estimated 621,937 live first births. The 0.012 coefficient on the variable of interest indicates 12 deaths in 1,000 livebirths. Thus, if district forest cover fell by one standard deviation in 2007, it would lead to 7,463 deaths among all the live first births in the study districts.[36] These deaths constitute 35 percent of

[36] As mentioned above, on average, a one standard deviation in annual district forest cover over the study period is 98 square kilometres.

the deaths that would have occurred among the first born children under the 2007 infant mortality rate in Indonesia (34 deaths among every 1,000 live births).

It should be kept in mind that the results of this study convey the implications of deforestation for infant mortality only within the specific context (Indonesia) and the timeframe (2000-2008) that I examine, and thus might not be widely generalizeable. Furthermore, the mortality costs identified by this research are very likely to be an understatement of the detrimental consequences of forest loss-induced malaria in Indonesia. I capture the mortality costs imposed upon one sub-group of infants—firstborn children, but am unable to do so for later born children who are also likely to suffer due to increased malaria, though to a lesser extent than the group I focus on. The results of several studies on the effects of early life exposure to malaria suggest that the disease leads to poorer adult health, lower educational attainment and reduced productivity among prime age workers (Hong, 2007; Barreca, 2010; Bleakley, 2010a; Cutler et al, 2010; Lucas, 2010; Barofsky et al, 2011; Chang et al, 2011; Percoco, 2013; Mora-Garcia, 2018).[37] The children who survived their infancy, despite being born to mothers infected with malaria amidst forest loss in Indonesia, might experience similar disadvantages in the future. In addition, the growth in malaria morbidities among school going and working populations in Indonesia is likely to have dampened other contemporaneous outcomes such as human capital acquisition and work productivity (Bleakley, 2010b).

In 2011, Indonesia announced a forest moratorium (which it subsequently revised and reissued it in 2013 and then again in 2015) to halt new concessions being granted for the logging and conversion of primary natural forests (and peatlands), and to improve the way in which these areas are governed (Murdiyarso et al, 2011; Ardiansyah et al, 2015). However, data suggest that deforestation appears to have spiked in the immediate aftermath of this moratorium (Margono et al, 2014). In strengthening national and regional anti-deforestation efforts, Indonesia can learn from the experiences of other countries. For instance, in recent years, Brazil has been able to substantially curb forest loss in the

[37] Many of these studies exploit the temporal variation in malaria exposure brought about by the introduction of a national malaria control or eradication program and the pre-intervention geographical variation in the prevalence of the disease within the country.

Amazon through conservation efforts. One of the adopted approaches uses a satellite system to detect deforestation activities as they are occurring (through satellite images generated every 15 days), thus enabling law enforcers to address illegal logging in real time (Assunção et al, 2015). Such strategies are needed particularly in Indonesia's primary forest regions, the degradation of which, as indicated by this and past research, might be most harmful for human health (Pattanayak et al, 2010; Garg, 2017).

Concurrently, Indonesia should intensify efforts to address the threats to health emerging due to forest deterioration and disappearance. As the current research demonstrates, one of these detrimental consequences is likely to be an increase in the burden of malaria. This calls for strategies such as those that have been used in successful malaria control initiatives around the world—the distribution of insecticide-treated bed nets, provision of prophylactic treatment to pregnant women and use of indoor residual spraying (Lucas, 2013; Pathania, 2014). In Indonesian districts losing forest cover and experiencing consequent spikes in malaria, women are more likely to experience poor birth outcomes during their first pregnancy and so young women should specifically be targeted by such preventive strategies.

This research shows that a subset of infants are facing a higher risk of dying in the face of forest loss in Indonesia, presumably due to concurrent increases in malaria. The malaria costs of the country's declining forest cover might thus be more severe than previously thought (Pattanayak et al, 2010; Garg, 2017). Concerted and speedy policy action is needed to address the rapid deforestation and environmental degradation taking place in Indonesia, as well as associated health concerns.

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Supplemental files

Appendix A

Table A1: Main Forest cover and infant mortality results with covariates

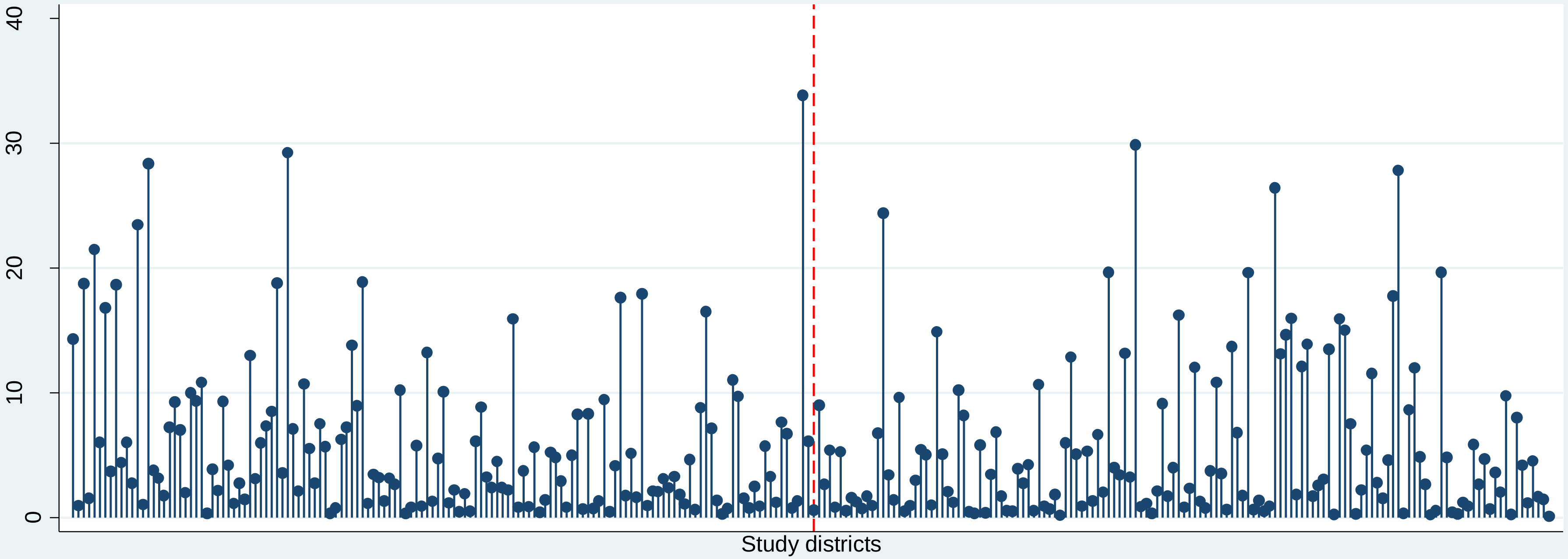
	Dependent variable: Infant mortality
Forest cover	0.009*
	(0.005)
First birth	0.002
	(0.005)
Forest cover*First birth	-0.012***
	(0.004)
Female	-0.008***
	(0.003)
Age of mother at birth of child	-0.008***
	(0.003)
Age of mother at birth of child^2	0.000***
	(0.000)
Mother's education (in years)	-0.001**
	(0.001)
Multiple birth	0.164***
	(0.033)
Rural residence	0.003
	(0.006)
Wealth index (Poorer vs. poorest)	-0.004
	(0.005)
Wealth index (Middle vs. poorest)	-0.000
	(0.006)
Wealth index (Richer vs. poorest)	0.005
	(0.006)
Wealth index (Richest vs. poorest)	-0.009
	(0.007)
DHS 2007 (vs. 2002)	0.036
	(0.027)
DHS 2012 (vs. 2002)	-0.009
	(0.023)
Precipitation	0.001
	(0.003)
Temperature	0.004
	(0.003)
Real GDP per capita	-0.013
	(0.008)
Observations	13,215
R-squared	0.046

Robust standard errors (clustered at the district-level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Forest cover during the year in which a woman spent her early pregnancy is measured as within district z-scores. The district fixed effects models include the following child-level controls: gender of the child, age of the mother at birth and its squared term, mother's education, and indicators for multiple birth, rural residence, wealth index and birth month. Other controls are island-year indicators, province-level linear time trends, DHS survey indicators, district-level precipitation and temperature z-scores, and per capita log real GDP. Sample includes children born 1-5 years before the DHS surveys. Mean infant mortality for all children and first born children are 0.035 and 0.037 respectively.

Table A2: Comparing the birth-level samples used for estimating the district fixed effects and maternal fixed effects specifications

	Women in district fixed-effects sample	Women in maternal fixed-effects sample	P-value of diff.
Woman's education (in years)	8.30	9.03	0.00
Residence in rural area	0.66	0.56	0.00
Wealth index	2.42	2.52	0.00
Woman's age	30.52	30.26	0.05
Muslim	0.82	0.78	0.04
Protestant	0.13	0.16	0.03
Catholic	0.04	0.04	0.53
Hindu	0.00	0.00	0.31
Observations	12,185	2,992	

P-values are reported from Wald tests on the equality of means between the two samples. Standard errors are clustered at the district level. Religion data is available only for 8,182 women in the district fixed effects sample and 833 women in the maternal fixed effects sample.



Notes: Each of the lines topped with a circle represents a district. Districts are arranged in ascending order of initial forest cover. The dashed line represents median initial forest cover. Lowest initial forest cover=0 square kilometers; Highest initial forest cover=45,071 square kilometers.

Figure A1: Examining District Forest Loss Between 2000 and 2008

(color to be used online only)

Appendix B

The following are the different forest cover measures used to probe the robustness of the main results (which are derived using within district z-scores):

1) Log deviation

$$Log\_dev_{dt} = \ln(annual\_forest_{dt}) - \ln(mean\_annual\_forest_{d}) \quad \text{Eq. (A.1.)}$$

2) More than one standard deviation below district mean

$$Low_{dt} = 1 \text{ if } annual\_forest_{dt} < (mean\_annual\_forest_{d} - st\_dev\_annual\_forest_{d})$$

$$= 0 \text{ otherwise} \quad \text{Eq. (A.2.)}$$

3) 80th & 20th percentiles

$$High\_low_{dt} = 1 \text{ if } annual\_forest_{dt} > 80p\_annual\_forest_{d}$$

$$= -1 \text{ if } annual\_forest_{dt} < 20p\_annual\_forest_{d}$$

$$= 0 \text{ if } 80p\_annual\_forest_{d} >= annual\_forest_{dt} >= 20p\_annual\_forest_{d} \quad \text{Eq. (A.3.)}$$

4) Level

Total land forested in a district in a year

where ln is the natural log, $annual\_forest_{dt}$ is total forest cover in district d in year t, $mean\_annual\_forest_{d}$ is average annual forest cover in district d between 2000 and 2008, $st\_dev\_annual\_forest_{d}$ is the standard deviation of annual forest cover between 2000 and 2008 in district d, $80p\_annual\_forest_{d}$ is the 80th percentile of annual forest cover in district d during the study period, and $20p\_annual\_forest_{d}$ is the 20th percentile.