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The Effects of Natural Disasters on Infant Health: Evidence from India

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a thesis submitted to the Faculty of Emory College of Arts and Sciences
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Abstract

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Given the rising frequency and intensity of natural disasters across the globe and particularly in developing nations, it is vital to understand the effect of climate on the health of future generations. I explore the effects of in utero exposure to tropical cyclones on birth outcomes in India by using spatial storm track data and representative demographic and health survey data. Difference-in-differences estimates indicate that exposure significantly increases neonatal and infant mortality rates, while the effect on birth weight is less clear. Heterogeneity analysis reveals that the negative consequences are most severe for those living in rural regions, evidencing the need for improved access to healthcare and stable infrastructure in India's rural areas. I highlight a combination of acute maternal stress and temporary shocks to healthcare services and infrastructure as plausible mechanisms.

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The Effects of Natural Disasters on Infant Health: Evidence from India

Danielle Handel

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1 Introduction

The impact of a changing climate on health and the economy is increasingly relevant to the navigation of a sustainable future in developing nations and across the globe. Extreme weather shocks in the form of natural disasters are useful natural experiments for understanding how the broader environment affects economic prospects: their incidence is exogenous, unrelated to the characteristics of those they affect, and their impacts can be immense, revealing relationships that may otherwise be difficult to identify. The impacts of tropical cyclones in particular are increasingly salient as they are predicted to become up to 34% more frequent and up to 11% more intense before 2100 (Knutson et al., 2010; Sobel et al., 2016). They also affect nearly one-third of the global population over the course of a lifetime (Hsiang and Narita, 2012), with their effects extending across generations.

As documented extensively by public health and international development organizations, women and children in developing countries are particularly vulnerable in the face of disaster (Fund, 2020; for Disease Control, 2020; Zeid et al., 2015). They face disproportionate negative health effects from natural disasters and are far more likely to die in the wake of disaster (Neumayer and Plümper, 2007; Frankenberg et al., 2011). Furthermore, unequal access to healthcare and relief resources exacerbates post-disaster disparities (Nour, 2011). This lack of access to proper women's health and maternal care assistance in the wake of natural disasters in developing nations has far-reaching effects for the human capital formation of future generations. Not only are women's acute maternal care needs in the wake of disaster not being met, but the effects of disaster are persistent in reducing the quality and availability of care for women and children.

In this paper, I aim to uncover the consequences of natural disasters on human capital formation and health that are not captured in official records of destruction or loss of life. I examine the effects of in utero tropical cyclone exposure on birth outcomes and infant health in India, a developing country which faces geographic challenges due to its frequent exposure to natural disasters such as tropical cyclones, typhoons, floods, and earthquakes, and demographic challenges due to its highly unequal population and lack of stable healthcare infrastructure and resources for its most impoverished citizens.

I use spatial data on tropical cyclone tracks in India in combination with three waves of Indian survey data on health behaviors and outcomes to analyze the effect of in utero exposure to tropical cyclones on infant and neonatal mortality as well as birth weight. My sample includes the children of respondents to the 1st, 2nd, and 4th waves of the Indian National Family Health Survey, and the birth years of these children span from 1980-2016. Survey information includes the district of residence of each mother, and I combine this with spatial storm track data to identify children whose district has been exposed to a tropical cyclone during their period of gestation. My empirical strategy exploits temporal differences in tropical cyclone landfalls and geographic differences in storm track paths. Using a difference-in-differences (DD) framework, I compare children within affected districts that have been exposed in utero to those born before or conceived after a storm and compare children born in exposed districts to those born in surrounding areas.

I find that in utero exposure to tropical cyclones of Category 1 or higher on the Saffir-Simpson scale leads to a 1.1 percentage point increase in probability of mortality within the first 28 days of life and a 2.2 percentage point increase in the probability of mortality within the first year of life. I also find no or minimal average effects of in utero exposure on birth weight or probability of being low-birth weight (<2500 grams). However, these effects on both mortality and birth weight are considerably heterogeneous with respect to various district-level and individual-level characteristics, mainly urban vs rural location, mother's age, and infant gender. The largest effects of tropical cyclones on neonatal and infant mortality occur in districts with larger rural populations and for children with younger mothers.

Broadly, I contribute to the literature examining the role of environmental shocks in infant health. My estimates for the effect of in utero storm exposure on birth weight align with the evidence from Currie and Rossin-Slater (2013) and Grabich et al. (2016) in the United States and Parayiwa and Behie (2018) in Australia that tropical cyclones have little effect on birth weight on average. My estimates of the impact of storm exposure on infant and neonatal mortality supplement those found by Anttila-Hughes and Hsiang (2013) in the Philippines and Oliveira, Lee, and Quintana-Domeque (2021) in Brazil. I specifically contribute to the literature examining this relationship in developing countries by providing the first estimates of the effects of tropical cyclones on birth outcomes in India. By doing this, I help provide context for India's notable struggle with fetal and maternal health outcomes and demonstrate that the findings of studies done in other developing countries have external relevance across the globe. Additionally, because many studies done in developing countries examine the effects of a single, exceptionally destructive, and unexpected disaster, I supplement these findings with analysis of many storms. This more accurately reflects the reality of economic life in India and many other developing countries, where natural disasters are more frequent than in developed countries. By examining the impacts of many storms in regions with continual storm exposure, I produce estimates that are particularly helpful in informing relief policies in the most affected areas.

I also provide context for the literature on the long-term effects of in utero exposure by exploring the impacts on early-life health as a potential pathway to longer-term effects on education, employment, and income. Because low birth weight has been demonstrated to have negative economic and health effects into later adulthood (Black, Devereux, and Salvanes, 2007), it is important to understand whether this is directly affected by natural disasters and is thus a feasible pathway for long-term impacts. Similarly, it is useful to understand whether in utero storm exposure leads to differential early mortality, which may mean that studies examining long-term effects will understate any negative consequences as they will not take into account the potential effects on the weakest children that lose their lives early due to exposure.

The rest of the paper proceeds as follows: Section 2 provides a review of the literature and context regarding the economic conditions in India, maternal and fetal and maternal healthcare in India, and the role of tropical cyclones in Indian life. Section 3 describes the data sources and presents descriptive statistics. Section 4 outlines the identification strategy used to analyze the impacts of tropical cyclones on birth outcomes. Section 5 presents the results of this analysis, Section 6 discusses potential mechanisms and heterogeneity, Section 7 provides robustness checks, and Section 8 concludes. Tables and figures are presented at the end of the paper.

2 Literature and context

In this section, I review the literature on the effects of natural disasters on children's health and human capital and provide context regarding the economic conditions in India, the environment of maternal and infant care in India, and the role of tropical cyclones in Indian life.

2.1 Literature on early life shocks and health outcomes

A growing body of literature in economics explores the short and long term effects of tropical cyclones and other climate events on a particularly vulnerable group: pregnant women and their children. This literature examines the effects of in utero and early-life exposure to natural disasters on short-term birth outcomes including mortality, birth weight, preterm births, and pregnancy complications, and long-term outcomes such as income, education level, and adult health. Behind this growing literature is both the need to understand the effects of climate on health, particularly for rising generations, and the continued investigation of the ways in which health generally responds to idiosyncratic shocks. The findings regarding the effects of hurricanes or tropical cyclones on birth outcomes and infant health are mixed and inconsistent (Jeffers and Glass, 2020), and while work on birth outcomes such as pregnancy complications and birth weight is more developed, there are relatively few studies that examine the effects of in utero exposure to tropical cyclones on neonatal on infant mortality (Oliveira, Lee, and Quintana-Domeque, 2021).

There is a breadth of work examining these relationships in the setting of developed countries. In the U.S., Currie and Rossin-Slater (2013) find significant effects of in utero exposure to hurricanes on the likelihood of pregnancy complications, C-sections, and preterm births, but do not find effects on birth weight. Simeonova (2011) finds significant reductions in birth weight and increased chances of preterm birth due to exposure to hurricanes in the second trimester. In the long-run, Karbownik and Wray (2019) demonstrate that hurricanes lower adult income for affected infants, attributed to a channel of reduced early-life health capital. Fuller (2014) also finds that in utero exposure leads to lower test scores, with the effects concentrated in disadvantaged groups.

Research on this phenomena in the developing world provides similar results. In the Philippines, Deuchert and Felfe (2015) study the impact of one, high intensity typhoon and find persistent, negative effects on children's education, but no effect on children's health or investments in children's health. Anttila-Hughes and Hsiang (2013) study several typhoons in the Philippines and find significant increases in infant mortality both in the year of the storm (due to in utero exposure) and in the years after the storm. Triyana and Xia (2018) also find significant effects on fetal loss due to in utero exposure to typhoons. In Brazil, Oliveira, Lee, and Quintana-Domeque (2021) find that infants exposed in utero have lower birth weights, are more likely to be low-birth weight, and are more susceptible to early-life mortality. In India, studies demonstrate that recent exposure to a variety of natural disasters including floods, earthquakes, and droughts affects early-life health by significantly reducing height-for-weight scores and immunization rates and increasing incidence of diarrhea (Datar et al., 2013). Droughts in particular are shown to cause declines in test scores with significant heterogeneity by familial socioeconomic status, noting that wealthier families in India are able to smooth negative shocks to income and resources in ways that are not provided through government relief. (Joshi, 2019).

A wide variety of other idiosyncratic shocks provide further evidence of the effect of crises on fetal health: studies examining earthquakes (Tan et al., 2009; Torche, 2011) and terrorist attacks (Brown, 2020; Mansour and Rees, 2011) found that in utero exposure to such crises can significantly reduce birth weight. Prenatal exposure to wildfire-induced air pollution in

Indonesia (Jayachandran, 2009) reduces the survival rate of fetuses, infants and children, and exposure to heightened civil war conflicts in Congo significantly reduced infant survival rates (Dagnelie, Luca, and Maystadt, 2018). Other work has identified that in utero exposure to radioactive fallout (Black et al., 2013; Almond, Edlund, and Palme, 2007) leads to lower levels of cognition and educational performance later in life.

2.2 Pathways between disasters and infant health

There are two main mechanisms through which natural disasters are hypothesized to affect fetal health: a biological channel of acute maternal stress and an economic channel of temporary negative shocks to the local economy, healthcare infrastructure, and individual income. The maternal stress pathway necessitates two distinct events: 1) exposure to a natural disaster causes significant increases in stress for an expecting mother and 2) the effects of this stress are passed on to the fetus. The incidence of this second event is well established: maternal exposure to stressful stimuli during pregnancy can have a wide variety of negative consequences on fetal health, including reduced birth weight and head circumference, fetal loss, birth defects, and preterm labor (Mulder et al., 2002; Coussons-Read, 2013). The evidence for the effect of exposure to natural disasters on maternal stress is limited in terms of direct measurements of biological stress responses (Ironson et al., 2014; Paxman et al., 2018), but several studies use indirect or self-reported measures of stress as evidence for this phenomena (Badakhsh, Harville, and Banerjee, 2010).

In addition to these individual effects on maternal stress and anxiety, natural disasters negatively shock economies and healthcare systems, leading to significant negative fiscal consequences that persist over time (Deryugina, 2017; Hsiang and Narita, 2012) and short-term individual earnings losses exacerbated by damage to homes and businesses (Groen, Kutzbach, and Polivka, 2020). Severe tropical cyclones may also lead to the closure or evacuation of hospitals (Adalja et al., 2014), overwhelming of the healthcare services infrastructure (Henderson et al., 1994; Takahashi et al., 2007) and the subsequent interruption of vital prenatal care (Sato et al., 2016). Natural disasters will exacerbate existing issues with less resilient healthcare infrastructure and existing economic hardships. As I will later argue, it is likely that the identified effects on infant health occur due to a combination of maternal stress and infrastructure and economic losses.

2.3 The Indian economy

India, a nation of 1.38 billion people as of 2021, had a GDP PPP per capita of approximately 6920 Int'l$ in 2020, which has grown from 533 Int'l$ over the period of interest from 1980-2020 according to World Bank estimates. In comparison, the GDP PPP per capita of the group of nations (including India) regarded by the International Monetary Fund as Emerging and Developing Asian Nations, has grown from 557 Int'l$ in 1980 to 11450 Int'l$ in 2020. While the World Bank estimates of total GDP PPP place India at third in the world behind only China and the United States with over 9.5 T Int'l$, 2020 estimates of GDP per capita PPP place India as 124th out of 186 globally, above Myanmar and Bangladesh for income per person, but below Brazil and the Philippines.

The population in India, which makes up about 1/5 of the world's total population, is growing at just over 1.1% per year, with India now standing as the second most populous nation on earth. According to World Bank estimates, just over 65% of India's population lives in rural areas, with 42% of the Indian workforce engaging in agricultural work. In the urban areas, populations are densely packed and income inequality is apparent in the infrastructure. The western coastal city of Mumbai, India's second most populous city with 20.4 million residents, is also the world's most densely populated city, with over 20,000 residents per square kilometer. Similarly, Delhi, India's central northern capital city, is its most populous with over 30.3 million residents and a population density of over 9,000 residents per square kilometer. As a consequence of this extreme density, data from the most recent Indian Census in 2011 indicate that over 17% of urban households are located in slums, residential areas defined by the Indian government as unfit for human habitation due to overcrowding, poor and unsafe infrastructure, and inadequate sanitation systems.

2.4 Healthcare infrastructure

Estimates from the World Bank also indicate that India's population as a whole is underserved by the healthcare infrastructure, with .7 government hospital beds per 1000 residents. This places India at 166th out of 186 globally. Quality of care is also higher in private hospitals, but these are concentrated almost exclusively in urban areas. Recent efforts beginning in the 1990s and accelerating with the 2005 National Rural Health Mission have led state governments to bolster healthcare capacity and infrastructure in rural areas, but only 10% of Indian doctors serve in government hospitals, so rural populations continue to struggle with access to care (Rajagopalan and Choutagunta, 2020), and poorer Indians continue to pay significantly more for similar health services, disincentivizing the poor and underserved from utilizing the few available services (Dash and Mohanty, 2019). There is considerable evidence that caste membership, tribal ethnicity, income, and wealth also affect access to and utilization of maternal healthcare in India (Ali and Chauhan, 2020).

The disparity in access and the lack of sufficient services to serve the growing population in India is reflected in its maternal and infant health outcomes. India is ranked 137th out of 186 by the World Bank for under-5 mortality with 34.3 deaths per 1000 live births, 28.3 infant deaths per 1000 live births, and 21.7 neonatal deaths per 1000 births. Of particular significance is India's maternal mortality rate, which stands at 130 maternal deaths per 100,000 live births, a statistic that the government aims to reduce to 70 in accordance with the United Nations Millennium Development Goals.

2.5 Tropical cyclones in India

The Indian peninsula, sandwiched between the Bay of Bengal on the east, the Arabian Sea on the west, and lying just north of the Indian Ocean, is situated in an area that is heavily conducive to powerful tropical cyclones. The geologic characteristics of the Bay of Bengal in particular, including its exceptionally warm waters, depth, and concavity, make it a prime breeding ground for the world's strongest storms (Biswas, 2020). Of the 36 deadliest tropical cyclones in history, 26 originated in the Bay of Bengal and 10 eventually made landfall with significant casualties in India. Over 3/4 of the storms in my sample originated in the Bay of Bengal, with the others originating in the less prolific Arabian Sea. As the largest bay in the world with over 500 million people living on the coast as of 2020, it has profound effects on the quality of life and long-term economic well-being of those in India, Bangladesh, Sri Lanka, and Myanmar. India is particularly at-risk, with over 5,700 kilometers of disaster-prone coastline.

3 Data

This paper combines spatial data on tropical cyclone tracks with district-level survey data on children and their mothers, including birth outcomes, demographic characteristics of the mother, fertility histories, and various facets of child and maternal health outcomes and behaviors.

3.1 Data on storms and cyclones

To construct the tropical cyclone paths, I use the "best track" data from the NOAA's International Best Track Archive for Climate Stewardship (IBTrACS) database for all storms in the North Indian Basin that made landfall in India. These data include estimates for the longitude and latitude coordinates of the eye of the storm and maximum sustained wind speeds at 3-hour intervals throughout the duration of each tropical storm. I restrict the timeline to 1977-2020 given that the birth years of the children in my sample range from 1980 to 2016, and I use classification scales identified by the World Meteorological Organization for storms in this region to define tropical cyclones as storms reaching sustained wind speeds of greater 64 knots. After joining these individual spatial entries into a continuous storm path, I measure distance from the population center of each district to the eye of each storm. Districts whose center of population lies within 50 kilometers of a tropical cyclone eye are considered to be fully exposed to that storm because this corresponds with the average size of the extent of the 50 knot+ winds of the storms in my sample. I show robustness of my effects to the convention of the 30 km buffer zone as used in previous literature for North Atlantic hurricanes (Currie and Rossin-Slater, 2013; Karbownik and Wray, 2019) to represent the average extent of the tropical cyclone's "eye wall," the area in which the wind speeds and rainfall are often most severe. I demonstrate robustness to various other definitions of exposure from 30 to 70 km in the Section 7 as well. In the main specification, control districts are defined as those with population centroids 50-100 km away from the eye of a storm. Using this specification, 73 districts out of the 349 districts for which data is available are ever within 50 km of a tropical cyclone, and 29 districts are included in the control group, within 50-100 km from the storm path. Over the 40-year period of interest, I record 51 tropical cyclones with sustained wind speeds equivalent to those of hurricanes of category 1 or higher on the Saffir-Simpson hurricane wind scale that came within less than 100 km of population centers of the districts included in my sample. The average maximum wind speed of these tropical cyclones is 97 knots, equivalent to a Category 2/3 storm on the Saffir-Simpson scale.

Though the most recent census in 2011 counts 640 districts in India, 87 new districts have since been added through splitting districts and changing administrative borders. In order to assess trends in district-wide outcomes over time, I use only the 349 districts whose borders have not changed significantly over the period of interest from 1980 to 2020 and for which I have information for all years of survey data as described in the next section. These modified districts are distributed across all regions of India, both coastal and inland, so their exclusion does not present any significant threat of bias.

3.2 Data on birth outcomes

Information on birth outcomes and mother and child characteristics comes from the 1992, 1998, and 2015 waves[1] of the Indian National Family Health Survey, accessed via IPUMS DHS. The survey consists of several separate samples, and I utilize the children sample, which reports birth weight and demographic characteristics for children born up to 5 years prior to the survey, for analyzing the effect of in utero tropical cyclone exposure on birth weight. This sample reports the exact birthday of each child. I use the births sample, which reports entire fertility histories for each mother in the sample, demographic characteristics, and birth month for each child, to measure effects on mortality. This sample does not provide exact birth dates, but does record birth months. Given the different sample sizes and level of detail regarding when a child was born, I model the effects on birth weight and on mortality using two distinct econometric specifications. I will expand upon this in Section 4.

[1] Due to privacy requirements for AIDS questionnaires, the third wave of the survey, conducted in 2005, does not include information about respondents' district of residence. Thus, I do not use survey data from the third wave.

3.2.1 Mortality data

I obtain data for infant and neonatal mortality from the retroactive fertility histories found in the births sample survey. This includes all births to female respondents aged 13-45 at the time of the survey for waves 1 and 2 and all female respondents aged 15-45 for survey wave 4. I limit the sample to include children with non-missing information regarding mother's district of residence, child's age, and child's age at death if deceased. The group of mothers used for analysis includes only those that ever lived within 100 km of a storm path, allowing for a more homogeneous sample. Table 1 presents the averages of core demographic characteristics for children and mothers in each sub-group of the sample, weighted using provided survey weights. Figure 1 illustrates the weighted size of the sub-sample in each district in the treatment and control groups. I find these groups to be balanced in the outcome variables of interest, namely neonatal mortality and infant mortality, meaning that underlying differences in mothers and children near or far from storm paths are unlikely to bias estimates. I do note that mothers in districts ever within 50 km of a storm path are more highly educated by less than 1 year and are more likely to be literate, have less children, and live in a rural area.

3.2.2 Birth weight data

I obtain data on birth weight from the children's survey sample, which includes records for children born to sampled respondents up to 5 years prior to the survey. Thus, the children in the sample are born in the years 1987-1998 and 2010-2016. The sample is limited to children living at the time of the survey with non-missing information about the child's date of birth, sex, birth weight, and district of residence. Notably, when removing children without measured birth weight, the sample size is reduced significantly. I do not find a significant causal relationship between the absence of a recorded birth weight and in utero exposure to tropical cyclones, which suggests that this reduction in the sample likely does not represent a significant bias of the estimates on birth weight due to exposed children not being weighed at birth. Still, the group of children that are not weighed are less wealthy and their mothers have lower education levels on average. As I will later address, birth weight information is not provided for deceased children. Figure 2 illustrates the weighted size of the sub-sample in each district in the treatment and control groups. Table 2 presents the weighted averages of core demographic characteristics for children and mothers in each sub-group of the sample. In this sample, I find that infants in districts that are ever within 50 km of a tropical cyclone path weigh 1.3% more than their control group counterparts and are 2 percentage points less likely to weigh less than 2500 grams. Their mothers are more educated, have less children, and are more likely to live in a rural area.

4 Identification strategy

4.1 Mortality specification

Given these underlying differences in the demographic characteristics of those affected by tropical cyclones, a simple comparison of birth outcomes will not reveal the causal effect of storm exposure. In order to capture this, my main empirical strategy is a difference-in-differences (DD) approach to estimate the effect of in utero tropical cyclone exposure on birth outcomes. The first source of variation is geographic, based on the mother's district of residence. The second source of variation is temporal, based on the infant's date of birth and estimated date of conception. Because exact birth dates are not provided in the births sample, I consider children whose mothers reside in districts whose population centers are within 50 km of a tropical cyclone within the 9 months before their birth to be exposed in utero. I also demonstrate the robustness of these results in Section 7 by executing analysis without births or conceptions in the month of a storm. I use a linear probability model to estimate the effect of in utero exposure on a) mortality within the first 28 days (neonatal mortality) and b) mortality within the first year (infant mortality). The model includes birth cohort, district, and state-by-year fixed effects, and to account for the assignment of exposure to whole districts, standard errors are clustered at the district level. This is modeled by equation (1):

$$Y_{idsmy} = \beta_0 + \beta_1(exposure_{dmy}) + \gamma_d + \delta_{my} + \eta_{sy} + X_i + Z_{dy} + \epsilon_{idsmy} \tag{1}$$

where the dependent variable Y_{idsmy} denotes the birth outcome for infant i born to a mother residing in district d and state s in month m and year y and $exposure_{dmy}$ is a binary variable taking on a value of 1 if the child's district d is within 50 km of a cyclone track during their period of gestation, defined as an estimated 9 month period. This model includes three sets of fixed effects: district FEs (γ), month-year birth cohort FEs (δ), and state-by-year FEs (η). Additional control variables are defined as follows: the vector X consists of individual infant and mother characteristics including sex of the child, birth order of the child, whether the child is a singleton, marital status of the mother, education level of the mother, mother's ethnicity/ caste membership, total children born to mother, and a household wealth index; the vector Z consists of district-survey year characteristics including female literacy, percentage of residents living in urban areas, and an average measure of wealth index.

4.2 Birth weight specification

I modify equation (1) to assess a) effect on birth weight and b) effect on the probability of being low-birth weight by modifying the level of detail regarding temporal exposure. Because the children's sample includes information regarding exact birth dates, I include time fixed effects for week-year birth cohort and code exposure at the week level for a given district. In the absence of exact dates of conception, I use the period of 39 weeks to serve as an estimation of the average gestational age, and thus assign in utero exposure to those impacted within the 39 weeks before their birth. As noted by Currie and Rossin-Slater (2013), this method of estimation may introduce bias on either end, with premature births being incorrectly assigned to exposure and children with longer gestational ages being more likely to be exposed to a hurricane due to mere length of time in utero. To address this, I demonstrate the robustness of my results using estimations of 37-41 weeks of average gestation period in Section 7. This modification is presented by equation (2):

$$Y_{idswy} = \beta_0 + \beta_1(exposure_{dwy}) + \gamma_d + \delta_{wy} + \eta_{sy} + X_i + Z_{dy} + \epsilon_{idswy} \tag{2}$$

where the dependent variable Y_{idswy} denotes the birth outcome for infant i born in district d and state s in week w and year y and $exposure_{dwy}$ is a binary variable taking on a value of 1 if the child's district d is within 50 km of a cyclone track during their period of gestation. This model includes three sets of fixed effects: district FEs (γ), week-year birth cohort FEs (δ), and state-by-year FEs (η).

5 Results

In this section, I present the results of estimations using the models identified in Section 4 as well as event study specifications to assess the effects of exposure at various times over the course of infant development and investigate the plausibility of the difference-in-differences parallel trends assumption.

5.1 Mortality results

I first examine the effects of in utero tropical cyclone exposure on mortality. Table 3 presents the estimates for the coefficient on in utero exposure, β_1 in equation 1. For neonatal mortality, these values represent the effect of in utero storm exposure on the probability of death within the first 28 days of life, and for infant mortality, they represent the effect of in utero storm exposure on the probability of death within the first year of life.

As evidenced by the estimated coefficients on exposure in the results column (2), which includes both fixed effects and individual- and district- level covariates, I find that in utero exposure to a tropical cyclone significantly increases the probability of death within the first 28 days by 1.1 percentage points and the probability of death within the first year of life by 2.2 percentage points. I identify strong dose-response effects: large positive effects from storms of Category 1 or higher, and no effects from less intense tropical storms[2]. It is not likely that these average effects on mortality are attributable to selective fertility due to tropical storm exposure as I find that birth rates are not affected by storm exposure on average. These results are discussed further in Section 7.

In Brazil, Oliveira, Lee, and Quintana-Domeque (2021) find that a single, high intensity storm increase the post-neonatal (29 days to 1 year) death rate by 4.2 per 1000 live births, representing approximately 18% of the baseline estimate of 22.5 post-neonatal deaths per 1000 births. I find an increase in post-neonatal deaths of 10.8 deaths per 1000 births, which represents approximately 25% of the 40.3 post-neonatal deaths per 1000 live births. Though the raw magnitude of my estimate is higher, it represents a similar increase in relation to the baseline post-neonatal death rate estimates, suggesting that the mechanisms that contribute to India's higher baseline death rates may similarly contribute to the larger negative consequences from in utero storm exposure. Thus, I hypothesize that the difference in these effect sizes can be attributed to lack of access to healthcare institutions and maternal care services that are prevalent in everyday life in India and exacerbated in the wake of

[2]These results are not included as this sampling does not provide additional information.

disaster. Given that poorer mothers tend to be more susceptible to increased stress levels due to extreme events such as tropical cyclones (Dunkel Schetter, 2011), the maternal stress pathway may also be strengthened due to India's comparatively poor population. In Section 6, I will show that this mechanism holds within India as well- the infants of rural, lower-SES mothers are disproportionately affected by in utero exposure to tropical cyclones.

5.2 Birth weight results

In addition to mortality, I also consider the effects of in utero exposure to tropical cyclones on birth weight, a less extreme measure of infant health. Table 4 presents the estimates for the coefficient on in utero exposure, β_1 in equation 2. For birth weight, these values represent the estimated percent change in birth weight due to storm exposure in utero. For low birth weight, the values represent the estimated change in probability that a given child weighs less than 2500 grams given in utero storm exposure. As evidenced by the estimated β_1 in the preferred specification in column (2), I do not find robust evidence that in utero exposure to tropical cyclones significantly affects either birth weight or the probability of being low-birth weight. While these estimates align with evidence identified by Currie and Rossin-Slater (2013) in the United States, work in other developing countries such as Brazil (Oliveira, Lee, and Quintana-Domeque, 2021) and Chile (Torche, 2011) has in fact identified negative effects of exposure on birth weight.

I attribute my findings to two phenomena: a) inaccurate reports of birth weight that do not reflect the true distribution of birth weights in the sample, and b) bias due to the identified trends in differential early mortality. The self-reported measures of birth weight provided in the children's sample survey reflect the possibility of "heaping," which involves either misreporting behaviors, such as unnecessary rounding and changing of values dependent upon a desired outcome, or lack of access to precise measuring tools which leads to some birth weight recorded at finer levels and others at coarser groups or bounds. This measurement error likely biases my estimates downwards, as the effect sizes would need to be larger for there to be statistically significant effects detectable in this setting.

Additionally, the magnitude of these estimated effects on birth weight may be downward biased given the differential rates of both infant and neonatal mortality due to storm exposure. Because birth weight is only reported for children alive at the time of the survey, I cannot examine the effects of storm exposure on the birth weight of deceased children. These children represent 7.9% of my respondents. I construct Lee bounds (Lee, 2009) given this likely non-random selection into the sample in Section 7, identifying that the magnitude of the effect of in utero exposure on birth weight depends on the birth weights of these children removed from the sample: if these children were on the lower end of the birth weight distribution at birth, the effect was likely negative, which aligns with the findings of Oliveira, Lee, and Quintana-Domeque (2021) in Brazil and Torche (2011) in Chile. This is discussed in further detail in Section 7.

5.3 Event studies

In order to examine any possible effects of exposure before conception or after birth and to contextualize my findings, I explore more granular levels of timing of exposure by including variables indicating exposure to a hurricane 19-36 months prior to birth, 10-18 months prior to birth, exposure in utero, exposure 1-6 months after birth, and 6-12 months after birth, corresponding with periods -2 through 2. This can be modeled by equation (3) for mortality outcomes and equation (4) for birth weight outcomes:

$$Y_{idsmy} = \alpha_0 + \alpha_k(\sum_{k=-2}^{2}(Period^k_{dmy}) + \gamma_d + \delta_{my} + \eta_{sy} + X_i + Z_{dy} + \epsilon_{idsmy} \tag{3}$$

$$Y_{idswy} = \alpha_0 + \alpha_k(\sum_{k=-2}^{2}(Period^k_{dwy}) + \gamma_d + \delta_{wy} + \eta_{sy} + X_i + Z_{dy} + \epsilon_{idswy} \tag{4}$$

where each α_k corresponds with a different period of exposure as detailed above. Figures 3 to 6 plot these effect sizes at various exposure times. For both infant and neonatal mortality, these plots demonstrate that exposure to a tropical cyclone 1-2 years prior to conception has no effect on mortality. However, exposure 0-9 months before conception does yield an upward effect on mortality rates. This further establishes infrastructure and economic losses as a pathway for storms to effect infant health: it is likely that damages that happen in this period persist into the next period, especially in poorer regions in which rapid relief and rebuilding is difficult, thus impacting children conceived in the months after. I do not identify any precisely estimated effects of post-birth exposure on mortality, suggesting children on average are most susceptible to these negative shocks while in the womb. This also helps to satisfy the assumption of parallel trends in outcomes necessary for the application of a difference-in-differences framework. I also find that post-birth exposure has no effect on birth weight or the probability of being low-birth weight, and impacts before conception and after birth are concentrated at zero.

6 Heterogeneity analysis

In order to identify potential mechanisms for the effects on neonatal and infant mortality and birth weight due to in utero exposure to tropical cyclones, I examine the differences in effects with respect to both district- and individual-level characteristics. To demonstrate the effect of storms on local economies and infrastructure, I focus on three proxies for district-level socioeconomic status: percentage of residents living in urban areas, average wealth, and female literacy rates. In examining the differences of effects in urban vs. rural areas, I focus on access to healthcare and economic infrastructure as a potential mediator for negative consequences of storm exposure on infant health. By assessing heterogeneity by district-level wealth, I consider whether areas with greater access to capital are able to smooth negative shocks more efficiently than those that are constrained. By observing potential differences in effects due to differing levels of female literacy, I investigate whether higher levels of female education can help limit the negative effects of storm exposure through storm preparedness or health literacy. To further explore the maternal stress pathway, I also examine heterogeneity by individual-level characteristics, namely mother's age and infant sex. By doing so, I examine two hypothesized mediators for stress response to crises.

6.1 District-level heterogeneity

I estimate the effect of exposure on mortality and birth weight using the models represented by equations (1) and (2) and report the estimated coefficients of the interactions between treatment and various measures of district-level SES. These results are reported in Tables 5 and 6. In both specifications, each sub-group is defined according to the district-level averages: rural districts are defined as those with less than the sample-wide average of residents living in urban areas, less wealthy districts are those whose average wealth index is below the sample-wide mean, and districts with low female literacy are those in which less than the sample-wide average of female respondents are literate.

The largest effects of in utero exposure on both infant and neonatal mortality occur in districts with rural populations. In these districts, the effect of storm exposure on the neonatal mortality rates of children is 2.8 percentage points higher, and the effects on infant mortality rates are 2.7 percentage points higher. Similarly, being exposed to a storm in utero lowers birth weight for children in rural areas by more than 4.5% more than their urban counterparts.

In fact, I find that the effects of storm exposure on both forms of mortality are small and negative for children in urban districts, and storm exposure actually leads to increased birth weight in urban districts. This means that for both measures of infant health, the expected effect is almost entirely driven by rural districts. This heterogeneity might be attributed to the disparities in both access to and quality of healthcare in rural vs. urban areas as highlighted in Section 2. Expecting mothers in districts with comparatively large rural populations rely on a small number of almost exclusively government-run care facilities, and the larger the rural population, the more these facilities can become overwhelmed and consequently unable to respond to environmental shocks both in terms of acute care in the wake of a disaster and in quickly returning to normal operations to resume continuous care, which is vital during pregnancy. As discussed earlier, this extended impact is highlighted in figures 3 and 4, in which I demonstrate that storm exposure 0-9 months prior to conception also has an effect on mortality outcomes. Additionally, families in these rural districts are less likely to have access to stable, well-constructed housing and utilities systems that are resilient to the rains and wind of tropical cyclones. As noted by Deuchert and Felfe (2015), effects of in utero exposure to tropical cyclones are likely moderated by access to such stable shelter.

I do not find significant heterogeneity by either wealth levels or female literacy, suggesting that neither a wealthy nor educated populace can overcome significant lack of access to the hospitals, sanitation systems, and rapid relief mechanisms in rural, under-served areas. Thus, the difference in effects on this dimension suggests that a temporary shock to access to services or infrastructure is a likely explanation for the impact of storm exposure on infant health.

6.2 Individual-level heterogeneity

At the individual level, I examine heterogeneity with respect to mother's age and infant sex. These results are shown in Tables 7 and 8. I find that the effects on both neonatal and infant mortality are larger for children with younger mothers, by 2.2 and 3.2 percentage points respectively. These negative consequences are also more apparent for birth weight and the probability of low birth weight, but this added effect is not precisely estimated. As evidence for the plausibility of the maternal stress pathway, this is consistent with the findings of Menclova and Stillman (2020), in which they highlight that younger mothers may be less equipped to deal with stressors and are thus more vulnerable to negative consequences. Oliveira, Lee, and Quintana-Domeque (2021) also find larger effects of in utero exposure on infant health for younger mothers.

Finally, as evident in Table 8, I identify infant sex as a source for heterogeneous effects. Male infants experience reductions in birth weight and increases in the probability of being low birth weight due to storm exposure, but these effects are not present for female infants. This is consistent with the fragile male hypothesis (Kraemer, 2000), which posits that male fetuses are biologically weaker and thus more vulnerable to increases in maternal stress and anxiety. However, I find virtually no difference in the effects of exposure on mortality for girls and boys. I attribute this to differential treatment of female infants because mortality is measured later in the child's life, when the effects of differential investment in girls may become apparent, thus moderating the biological female advantage.

7 Robustness

7.1 Fertility

All estimates of the effects of infant health are at risk for contamination due to selective fertility. In order to test whether certain mothers are choosing not to have children due to storm exposure, I examine the effect of tropical cyclone exposure within a year on the size of a birth cohort, defined as the number of live births in a district in a given month divided by the number of women ages 15-45 in that district-year sample. Because this is defined at the district-level and not at the individual level, I modify the main specification in equation (1) as modeled in equation (5):

$$Y_{dsmy} = \beta_0 + \beta_1(exposure_{dmy}) + \gamma_d + \delta_{my} + \eta_{sy} + Z_{dy} + \epsilon_{dsmy} \tag{5}$$

where Y is the live birth rate in district d and state s in month m and year y. Exposure is coded at the district level, and the model includes district fixed effects (γ), month-year fixed effects (δ), and state-by-year fixed effects (η). Z is a vector of time-varying district covariates.

As evidenced in Table 10, storm exposure in the past year has a very small, positive effect on the birth rate, meaning that average estimates are unlikely to be contaminated due to selective fertility. However, I do note that the effect of storm exposure on the birth rate for mothers in rural areas is larger and negative at a decrease of 4 babies per 1000 women, meaning that some of these mothers may have chosen to forgo having children due to reduced expectations of their ability to provide for a larger family because of economic losses from a storm. This is logical due to the often devastating effects of tropical cyclones on agricultural lands, and this means that some of my results could envelop fertility changes. Because I cannot identify which mothers are making these decisions, I propose two separate scenarios: if mothers with lower unobserved quality are choosing not to have children, then my estimates of the effect on mortality likely serve as an upper bound. If, conversely, these mothers are of higher quality, then my mortality estimates, particularly in rural areas, may be partially explained by changes in fertility.

7.2 Fetal mortality

While my results demonstrate that in utero exposure to tropical cyclones can affect mortality post-birth, the relationship between exposure and fetal losses is more difficult to identify because I do not have information regarding fetal deaths as only live births are reported. To investigate the possibility of tropical cyclones causing increased loss during pregnancy, I adopt the methodology used by Triyana and Xia (2018) by examining the effect of tropical cyclone exposure on the fraction of males in a given birth cohort. I use the model outlined in equation (5) and results are presented in Table 9. Though not precisely estimated, these negative effects are consistent with the fragile male hypothesis, which argues that the biological fragility of the male fetus makes it such that males are more susceptible to negative early life shocks than females in the womb (Kraemer, 2000). Thus, any unobserved effects on fetal mortality would be disproportionately present in male fetuses, thus reducing the fraction of males in the birth cohort. Triyana and Xia (2018) also find that in utero exposure to typhoons in the Philippines reduces the fraction of males in the birth cohort, though their estimated effect sizes are larger.

7.3 Lee bounds

Because birth weight is not observed for children that passed away prior to each survey, it is possible that estimates of the effects of storm exposure on birth weight are biased due to the plausibly non-random selection of children alive at the time of the survey. In order to address this, I construct Lee bounds (Lee, 2009) on the effect size, re-estimating the effects with imputed birth weights for these children. Because these children represent 8% of my sample, I use the model in equation (2) to estimate the effects of in utero storm exposure on birth weight imputing either a) the 5th percentile birth weight in the sample-wide distribution or b) the 95th percentile birth weight. These estimates, presented in Table 11, indicate that estimates would likely be negative if the children that did not survive to the survey date were weaker infants, which is a reasonable assumption. As evidenced by the estimates in Table 12, the heterogeneous effects identified in the main specification are also present, but they are not precisely estimated.

7.4 Varying measures of exposure

In my main specification, I assign exposure to a tropical cyclone if a district's population center is within 50 km of the storm path. In Table 13, I demonstrate that these results are robust to various different estimated radii from 30 km to 70 km.

In order to account for possible fuzziness at the boundary of these exposure radii, I also perform estimation using a ”donut hole” approach, in which I assign exposure to districts whose population centers lie 0 to d kilometers away from the storm path at various levels of d from 30-70, then drop districts between d and d+10 km from the storm path, finally assigning districts between d+10 and 100 km away from the storm path to the control group. These estimates are provided in Table 14, again demonstrating robustness to variation in definition of exposure.

7.5 Varying estimations of average length of gestation

Because the retroactive fertility histories used for analyzing the effect of in utero tropical cyclone exposure on mortality do not contain information regarding the exact birth date of each child, I assign children to exposure based upon their birth month. This means that, for example, a child born in the beginning of January may be assigned to the treatment group for in utero exposure to a tropical cyclone occurring on January 15th. Similarly, a child conceived on January 15th may be assigned to the treatment group for a tropical cyclone occurring on January 1st. Table 15 presents a comparison of the estimated effect sizes obtained from my main specification with effect sizes estimated by not including children born in or conceived in the month of a storm, demonstrating that my results are robust to these exclusions.

Similarly, because I do not have information regarding gestational ages for respondents in the children sample, I assume an average gestational length of 39 weeks for the purpose of analyzing the impact of in utero storm exposure on birth weight. In Table 16, I demonstrate that the effects are consistent across various different specifications of the average gestational length from 37 weeks to 41 weeks.

8 Conclusions

Natural disasters have impacts that go far beyond property damage and immediate loss of life, and it is important to identify these in order to protect global populations in a changing climate with more intense and frequent disasters. I examine the role of environmental shocks in determining infant health by analyzing the effects of in utero exposure to tropical cyclones in India on neonatal mortality, infant mortality, and birth weight. By employing a difference-in-differences technique, I exploit differences in the timing and location of tropical cyclone paths to isolate the effect of in utero exposure. I find minimal, insignificant effects of in utero exposure on birth weight and a significant 1.1 pp increase in the probability of death within the first 28 days of life or a 2.2 pp increase in the probability of death within the first year. These effects vary greatly for different socioeconomic groups, with children born in rural districts or to younger mothers at the greatest risk of facing negative consequences of in utero exposure. This heterogeneity suggests temporary shocks to access to healthcare infrastructure and other services along with high incidence of disaster-induced maternal stress in younger, low-SES mothers as potential explanations for the effect of exposure on infant health. Through the identification of this heterogeneity, I provide evidence for the need to target disaster relief aid and preparation to rural communities. Further, given continual global efforts to reduce infant and maternal mortality rates in developing nations via the UN Sustainable Development Goals, I highlight effective post-disaster relief with a focus on women and children as an avenue to reaching this goal.

Sample limitations due to heaping or lack of access to precise measurement tools likely hindered precise estimation of the effects of in utero storm exposure on birth weight and the probability of being low birth weight. This underscores the importance of investing in access to more sensitive measurement tools and more high quality data in developing nations. The continual growth in availability of granular demographic and health data in developing countries shows promise for future studies of this phenomena, but progress must continue if we are to develop data-driven and scalable policy tools to combat poor infant health and early mortality. Critically, further research is also needed to continue to tease out the channels through which infant health is affected by hurricane exposure. Identifying these mechanisms is vital to developing efficient disaster relief policies.

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9 Tables

	All in sample	0-100 km	50-100 km	0-50 km	Diff.
N	237,947	69,225	18,914	50,311	
Neo. Mortality	0.03	0.03	0.03	0.03	0.00
Inf. Mortality	0.05	0.04	0.04	0.04	-0.00
Female	0.48	0.48	0.47	0.48	0.01^{**}
Children born to mother	2.74	2.36	2.51	2.31	-0.20^{***}
Mother years of education	5.21	6.30	6.12	6.37	0.25^{***}
Mother literate	0.56	0.67	0.66	0.68	0.02^{***}
Scheduled caste or tribe	0.15	0.16	0.16	0.16	-0.00
Mother married	0.99	0.98	0.98	0.99	0.00
Urban	0.26	0.33	0.38	0.32	-0.06^{***}

Note: $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Table 1: Births sample descriptive statistics

This table presents the weighted averages of the outcomes of interest as well as several core demographic characteristics by sub-sample. The first column presents these statistics for all children in the births sample in India for survey waves in 1992, 1998, and 2015, while the second column limits the sample to only those residing in districts whose population centers have ever been within 100 km of a tropical cyclone. Columns 3 and 4 further divide this group into the control group that contains children residing in districts that come within 50-100 km of a tropical cyclone path and the ever-treated group whose districts do come within 50 km of a tropical cyclone. The last column presents the difference between the values in the ever-treated and control groups. The statistical significance of this difference is identified using a weighted t-test.

	All in sample	0-100 km	50-100 km	0-50 km	Diff.
N	143,507	50,224	13,511	36,713	
Birth weight	2797.98	2812.25	2785.21	2822.20	36.99^{***}
Low birth weight	0.19	0.18	0.19	0.17	-0.02^{***}
Female	0.47	0.48	0.47	0.48	0.01
Children born to mother	2.28	2.08	2.19	2.03	-0.16^{***}
Mother years of education	7.15	7.79	7.65	7.84	0.19^{***}
Mother literate	0.73	0.80	0.79	0.80	-0.01
Scheduled caste or tribe	0.14	0.15	0.16	0.15	-0.01
Mother married	0.99	0.99	0.99	0.99	0.00
Urban	0.34	0.40	0.45	0.38	-0.08^{***}

Note: $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Table 2: Child sample descriptive statistics

This table presents the weighted averages of the outcomes of interest as well as several core demographic characteristics by sub-sample. The first column presents these statistics for all children in the children's sample in India for survey waves in 1992, 1998, and 2015, while the second column limits the sample to only those residing in districts whose population centers have ever been within 100 km of a tropical cyclone. Columns 3 and 4 further divide this group into the control group that contains children residing in districts that come within 50-100 km of a tropical cyclone path and the ever-treated group whose districts do come within 50 km of a tropical cyclone. The last column presents the difference between the values in the ever-treated and control groups. The statistical significance of this difference is identified using a weighted t-test.

	A. Effect on Probability of Neonatal Mortality	
	(1)	(2)
Tropical cyclone in utero	.008*	.011**
	(.005)	(.005)
Covariates		✓
N	160,006	160,006
	B. Effect on Probability of Infant Mortality	
Tropical cyclone in utero	.019***	.022***
	(.004)	(.005)
Covariates		✓
N	160,006	160,006

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 3: Mortality results

This table presents the estimated effects of in utero tropical cyclone exposure on the probability of death within the first 28 days and the probability of death within the first year. Column 1 presents the results of the estimation done without covariates, while column 2 presents the results of the estimation done including district, state-by-year, and month-year fixed effects and individual and time-varying district level fixed effects. The estimated coefficients on exposure in panel A can be interpreted as the percentage point change in the probability of neonatal mortality due to in utero storm exposure. The coefficients in panel B can be interpreted as the percentage point change in the probability of infant mortality.

	A. Effect on Log(Birth Weight)	
	(1)	(2)
Tropical cyclone in utero	.007	.006
	(.015)	(.016)
Covariates		✓
N	17,890	17,890
	B. Effect on Probability of Low Birth Weight (<2500 grams)	
Tropical cyclone in utero	−.008	−.008
	(.048)	(.047)
Covariates		✓
N	17,890	17,890

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 4: Birth weight results

This table presents the estimated effects of in utero tropical cyclone exposure on birth weight and the probability of being low-birth weight. Column 1 presents the results of the estimation done without covariates, while column 2 presents the results of the estimation done including district, state-by-year, and month-year fixed effects and individual and time-varying district level fixed effects. The estimated coefficients on exposure in panel A can be interpreted as the percent change in birth weight due to in utero storm exposure. The coefficients in panel B can be interpreted as the percentage point change in the probability of being low-birth weight.

	Effect on Neonatal Mortality			Effect on Infant Mortality		
	(1)	(2)	(3)	(4)	(5)	(6)
exposed	−.010*	.011*	.009	−.003	.020**	.012
	(.005)	(.006)	(.009)	(.010)	(.008)	(.015)
exposed × high rural pop.	.028***			.027**		
	(.007)			(.013)		
exposed × low wealth		−.005			−.009	
		(.011)			(.012)	
exposed × low female literacy			−.0010			.008
			(.014)			(.025)
N	160,006	160,006	160,006	160,006	160,006	160,006

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 5: District-level heterogeneity of mortality effects

This table presents the estimates of the district-level heterogeneity of the effects of in utero storm exposure on neonatal mortality (within the first 28 days) and infant mortality (within the first year). This heterogeneity is identified by examining the estimated coefficients on the terms interacting a binary variable indicating lower-than-average measures of district-wide socioeconomic status. Column 1 presents the effect of exposure in urban areas and the additional effect for children in rural areas. The sum of these values provides an estimate of the effect of in utero exposure in rural districts. Columns 2 and 3 repeat this for columns with low wealth and low female literacy, and columns 4-6 repeat these with infant mortality as the outcome variable.

	Effect on Log(Birth Weight)			Effect on p(Low Birth Weight)		
	(1)	(2)	(3)	(4)	(5)	(6)
exposed	.022**	.007	.013	−.025	−.006	−.015
	(.008)	(.009)	(.009)	(.019)	(.016)	(.018)
exposed × high rural population	−.045***			.040		
	(.015)			(.029)		
exposed × low wealth		−.008			−.020	
		(.017)			(.033)	
exposed × low female literacy			−.022			.014
			(.017)			(.034)
N	17,980	17,980	17,980	17,980	17,980	17,980

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 6: District-level heterogeneity of birth weight effects

This table presents the estimates of the heterogeneity of the effects of in utero storm exposure on the log transformation of birth weight and the probability of being low birth weight (< 2500 grams). This heterogeneity is identified by examining the estimated coefficients on the terms interacting a binary variable indicating lower-than-average measures of district-wide socioeconomic status. Column 1 presents the effect of exposure in urban areas and the additional effect for children in rural areas. The sum of these values provides an estimate of the effect of in utero exposure in rural districts. Columns 2 and 3 repeat this for low wealth and low female literacy, and columns 4-6 repeat these with probability of low birth weight as the outcome variable.

	Effect on Neonatal Mortality		Effect on Infant Mortality	
	(1)	(2)	(3)	(4)
exposed	.001	.008	.008	.023*
	(.006)	(.010)	(.008)	(.013)
exposed × young mother	.022*		.032*	
	(.012)		(.018)	
exposed × female infant		.005		−.003
		(.016)		(.022)
N	160,006	160,006	160,006	160,006

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 7: Individual-level heterogeneity of mortality effects

This table presents the estimates of the individual mother- or child-level heterogeneity of the effects of in utero storm exposure on neonatal mortality (within the first 28 days) and infant mortality (within the first year). This heterogeneity is identified by examining the estimated coefficients on the terms interacting a binary variable indicating either a younger-than-average mother or a female infant. Column 1 presents the effect of exposure for infants with older mother and the additional effect for children with younger mothers. The sum of these values provides an estimate of the effect of in utero exposure for younger mothers. Column 2 repeats this for with female infants, and columns 3-4 repeat these with infant mortality as the outcome variable.

	Effect on Log(Birth Weight)		Effect on p(Low Birth Weight)	
	(1)	(2)	(3)	(4)
exposed	.009	−.009	−.026	.009
	(.012)	(.010)	(.020)	(.017)
exposed × young mother	−.006		.028	
	(.014)		(.029)	
exposed × female infant		.031**		−.039*
		(.013)		(.022)
N	17,980	17,980	17.980	17,980

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 8: Individual-level heterogeneity of birth weight effects

This table presents the estimates of the individual mother- or child-level heterogeneity of the effects of in utero storm exposure on the log transformation of birth weight and the probability of being low birth weight (< 2500 grams). This heterogeneity is identified by examining the estimated coefficients on the terms interacting a binary variable indicating either a younger-than-average mother or a female infant. Column 1 presents the effect of exposure for infants with older mother and the additional effect for children with younger mothers. The sum of these values provides an estimate of the effect of in utero exposure for younger mothers. Column 2 repeats this for with female infants, and columns 3-4 repeat these with probability of low birth weight as the outcome variable.

	Effect on Male Fraction of Birth Cohort			
exposed	$-.023$	$-.045^{*}$	$-.020$	$-.027$
	(.021)	(.023)	(.030)	(.029)
exposed × high rural population		.056		
		(.042)		
exposed × low wealth			$-.006$	
			(.049)	
exposed × low female literacy				.010
				(.036)
N	24,079	24,079	24,079	24,079

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 9: Effect of storm exposure on male fraction of birth cohort
This table presents the estimated effects of in utero tropical cyclone exposure on the percentage of a given district-by-month birth cohort that is male. The first column presents these effects on average, and the provided coefficient can be interpreted as the percentage point change in the male fraction of the birth cohort. Columns 2-4 examine the district-level socioeconomic heterogeneity of these results by presenting the effect size for high SES individuals and the additional effect on top of this for the low SES individuals. The sum of these provides an estimate for the total effect on low SES individuals.

	Effect on Fertility			
exposed	.002	.003	$.005^{**}$	.0003
	(.001)	(.002)	(.002)	(.0008)
exposed × high rural population		$-.007^{***}$		
		(.001)		
exposed × low wealth			$-.003$	
			(.002)	
exposed × low female literacy				.003
				(.002)
N	24,079	24,079	24,079	24,079

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 10: Effect of storm exposure on fertility
This table presents the estimated effects of in utero tropical cyclone exposure on district-by-cohort birth rate. The first column presents these effects on average, and the provided coefficient can be interpreted as the percentage point change in the birth rate. Columns 2-4 examine the district-level socioeconomic heterogeneity of these results by presenting the effect size for high SES individuals and the additional effect on top of this for the low SES individuals. The sum of these provides an estimate for the total effect on low SES individuals.

	Effect on Log(Birth Weight)	
	Lower	Upper
Tropical cyclone in utero	−0.015	0.028
	(0.011)	(0.018)
N	19,433	19,433

Note: $^{*} p < 0.1$; $^{**} p < 0.05$; $^{***} p < 0.01$

Table 11: Lee bounds on birth weight effects

This table presents the average effects of in utero exposure to a tropical cyclone on the log transformation of birth weight using imputed values for children with unobserved birth weight due to early mortality. The first column provides the estimate of in utero exposure on log(birth weight) when imputing the 5th percentile birth weight, 2000 grams, for these children, who represent 7.9% of the overall sample. The second column presents the estimate on log(birth weight) when imputing the 95th percentile birth weight, 4000 grams. These estimates provide a bound on the estimate for the effect on birth weight given that the sample is non-randomly selected to not include deceased children.

	Effect on Log(Birth Weight)					
	Lower	Upper	Lower	Upper	Lower	Upper
exposed	−.005	.051**	−.016	.038**	−.066	.056
	(.020)	(.022)	(.017)	(.015)	(.050)	(.052)
exposed × high rural population	−.016	−.039				
	(.024)	(.039)				
exposed × low wealth			.001	−.018		
			(.020)	(.032)		
exposed × low female literacy					.054	−.029
					(.051)	(.053)
N	19,433	19,433	19,433	19,433	19,433	19,433

Note: $^{*} p < 0.1$; $^{**} p < 0.05$; $^{***} p < 0.01$

Table 12: Lee bounds by SES

This table presents the average effects of in utero exposure to a tropical cyclone on the log transformation of birth weight using imputed values for children with unobserved birth weight due to early mortality. The first column in each set provides the estimate of in utero exposure on log(birth weight) when imputing the 5th percentile birth weight, 2000 grams, for these children, who represent 7.9% of the overall sample. The second column in each set presents the estimate on log(birth weight) when imputing the 95th percentile birth weight, 4000 grams. For each of these sets of columns, the effect size for high SES districts is provided in the first row and the additional effect for low SES individuals is provided in the next non-empty row. These estimates provide a bound on the estimate for the effect on birth weight given that the sample is non-randomly selected to not include deceased children.

Exposure definition	A. Neonatal mortality	B. Infant mortality	C. Log(Birth weight)	D. p(Low birth weight)
0-30 km	.009	.016***	.009	−.008
	(.005)	(.005)	(.016)	(.049)
0-40 km	.012**	.019***	.008	−.007
	(.005)	(.009)	(.016)	(.049)
0-50 km	.011**	.022***	.007	−.007
	(.005)	(.005)	(.016)	(.048)
0-60 km	.014**	.025***	.007	−.005
	(.006)	(.006)	(.016)	(.047)
0-70 km	.016***	.026***	.0009	.016
	(.006)	(.006)	(.017)	(.041)
N	160,006	160,006	17,980	17,980

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 13: Various definitions of exposure

This table presents the effects of in utero exposure to tropical cyclones using varying definitions of geographic proximity to a storm path. The main specification in this paper assigns exposure to a tropical cyclone if a district's center of population is within 50 kilometers of the path of the eye of the storm. Here, results with modifications of this definition are presented.

	Cyclone exposure dropping [d, d+10 km] region				
	30 km	40 km	50 km	60 km	70 km
	A. Probability of Neonatal Mortality				
Tropical cyclone in utero	.009	.012**	.011**	.014**	.016***
	(.005)	(.005)	(.005)	(.006)	(.006)
N	153,570	160,006	153,718	151,052	144,136
	B. Probability of Infant Mortality				
Tropical cyclone in utero	.016***	.019***	.022***	.024***	.026***
	(.005)	(.005)	(.005)	(.006)	(.006)
N	153,570	160,006	153,718	151,052	144,136
	C. Log(Birth weight)				
Tropical cyclone in utero	.009	.008	.007	.012	.007
	(.016)	(.016)	(.016)	(.016)	(.017)
N	17,268	17,980	17,313	17,158	16,105
	D. Probability of low birth weight				
Tropical cyclone in utero	−.007	−.007	−.010	.0003	.008
	(.048)	(.049)	(.048)	(.049)	(.039)
N	17,268	17,980	17,313	17,158	16,105

Note: $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Table 14: Exposure assignment using donut holes

This table presents the estimated effects of in utero storm exposure on all outcomes of interest using a "donut" method of classifying geographic exposure. In column 1, the exposed region is identified as those districts whose population centers are within 30 km of a tropical cyclone path and the control districts are those that lie 40-100 km from a tropical cyclone path. The districts that lie 30-40 km from a cyclone path are dropped from this analysis as it may be unclear whether they are treated by the cyclone or not. This is repeated in the subsequent columns for 40-70 km. Panel A provides estimates of the effect on birth weight, and these can be interpreted as the percent change in birth weight due to exposure. Panel B provides estimates of the effect on the probability of being low-birth weight, and Panels C and D represent the effects on neonatal and infant mortality. For all of these, the value can be interpreted as the percentage point increase in probability.

	A. Neonatal mortality	B. Infant mortality
Keep all	.011**	.022***
	(.005)	(.006)
Drop edges	.009**	.017***
	(.004)	(.006)
N	160,006	160,006

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 15: Dropping edge births for mortality effects
This table presents the effects of in utero exposure to tropical cyclones on neonatal mortality and infant mortality, taking into account that the exact day of birth is not observed in this sample. In the first row, I provide estimates using the main specification in which children are considered to be exposed if a tropical cyclone affects their district within the 9 months before their birth. In the second row, I present estimates of the effect on mortality when dropping children born or conceived in the month of a storm, taking into account the fact that they may have been incorrectly assigned to the treatment group.

	37 weeks	38 weeks	39 weeks	40 weeks	41 weeks
			A. Effect on Log(Birth weight)		
in utero exposure	0.007	0.006	0.006	0.006	0.006
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Mean of Y					
N	17,980	17,980	17,980	17,980	17,980
			B. Effect on p(Low birth weight)		
in utero exposure	−0.006	−0.006	−0.006	−0.006	−0.006
	(0.048)	(0.047)	(0.047)	(0.047)	(0.047)
N	17,980	17,980	17,980	17,980	17,980

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 16: Birth weight estimates with varying average gestation lengths
This table presents the effects of in utero exposure to tropical cyclones on both birth weight and the probability of being low-birth weight (<2500 grams) using different estimates for the average length of gestation. 39 weeks is used in the main specification, and for each other estimate, this changes the way in which exposure is defined. For example, with an estimate of 37-week average gestational period, infants are classified as exposed in utero if their district is within 50 km of the storm path at any point during the 37 weeks before their birth. For birth weight, the estimates shown represent the percent change in birth weight, and for low birth weight, the estimates represent the percentage point change in the probability of a newborn being low-birth weight.

10 Figures

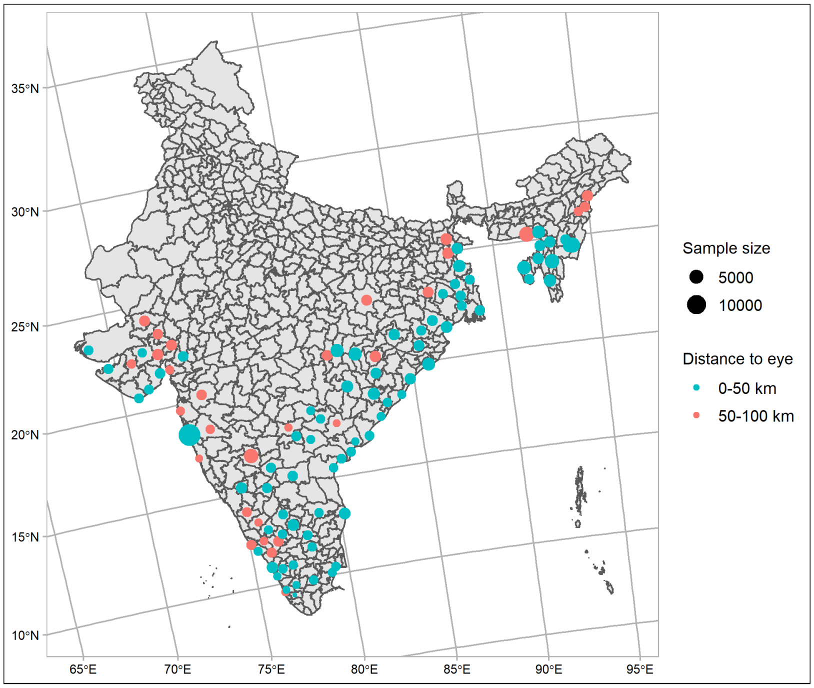

Figure 1: Mortality sample mapping

This figure presents the sizes of each sub-sample of the births sample, which is used to estimate the effects of storm exposure on mortality. The sample sizes are weighted by provided survey weights to ensure that the samples are representative. Markers are placed on the population centers of their respective districts.

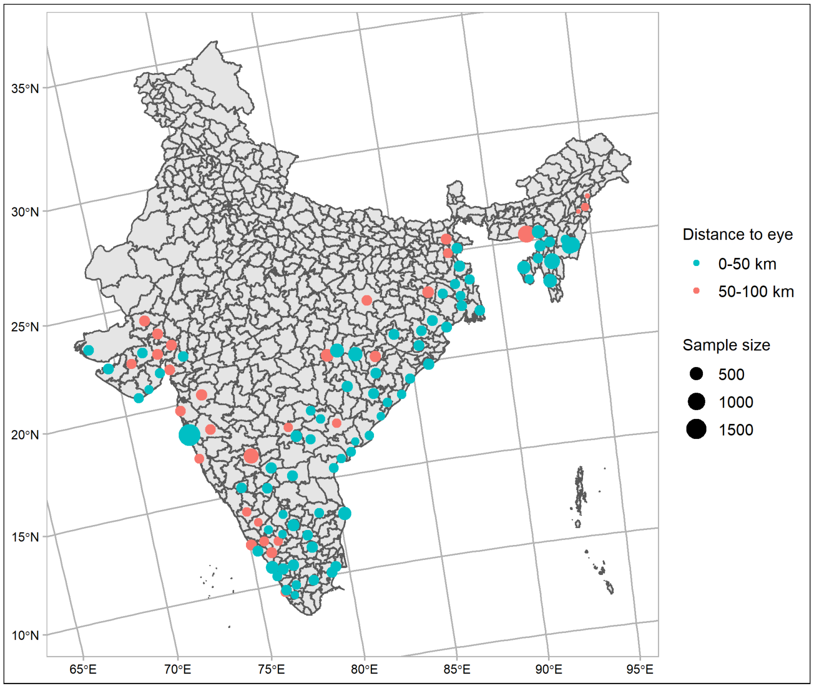

Figure 2: Birth weight sample mapping
This figure presents the sizes of each sub-sample of the children's sample, which is used to estimate the effects of storm exposure on birth weight. The sample sizes are weighted by provided survey weights to ensure that the samples are representative. Markers are placed on the population centers of their respective districts.

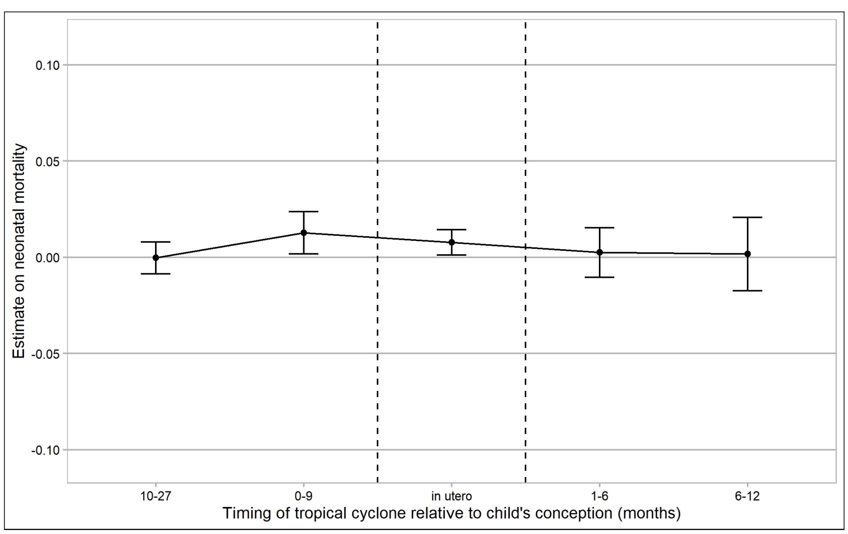

Figure 3: Effect size by exposure timing- neonatal mortality
This figure presents the estimates of the effect of tropical cyclone exposure at varying stages of development on the probability of death within the first 28 days of life. The error bars represent a 95% confidence interval about the given point estimate.

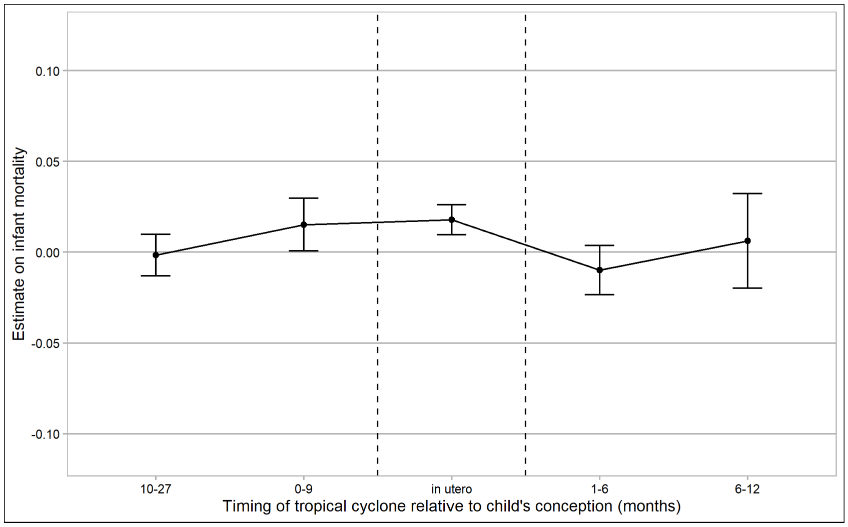

Figure 4: Effect size by exposure timing- infant mortality
This figure presents the estimates of the effect of tropical cyclone exposure at varying stages of development on the probability of death within the first year of life. The error bars represent a 95% confidence interval about the given point estimate.

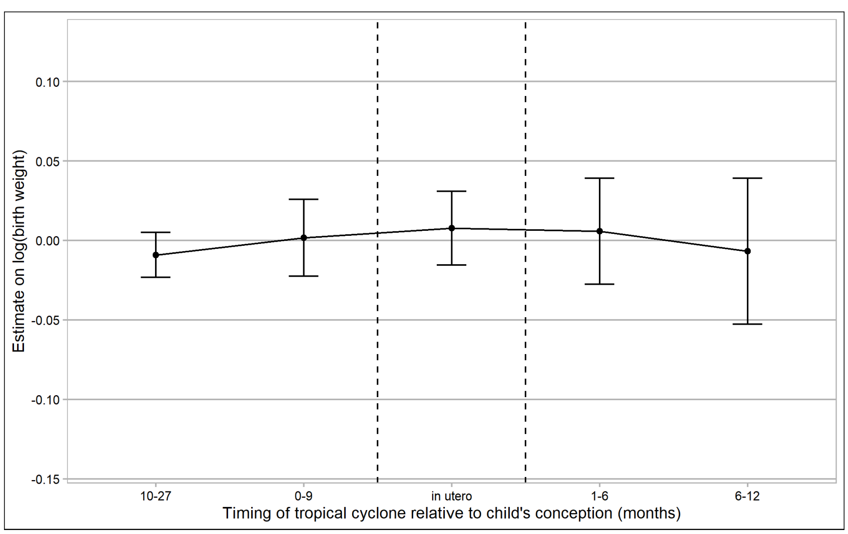

Figure 5: Effect size by exposure timing- birth weight
This figure presents the estimates of the effect of tropical cyclone exposure at varying stages of development on infant birth weight. The error bars represent a 95% confidence interval about the given point estimate.

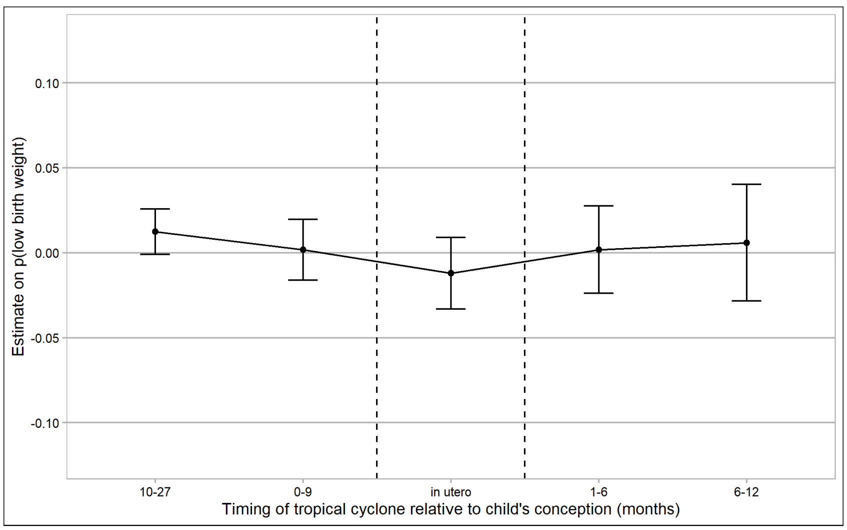

Figure 6: Effect size by exposure timing- low birth weight
This figure presents the estimates of the effect of tropical cyclone exposure at varying stages of development on the probability of an infant being low-birth weight (< 2500 grams). The error bars represent a 95% confidence interval about the given point estimate.