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The Long-run Effects of Tropical Cyclones on Infant Mortality

Isabel Miranda
miranda.isabel731@gmail.com

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Isabel Miranda

Advisor: Professor Jesse Antilla-Hughes

Department of Economics
University of San Francisco
2130 Fulton St.
San Francisco, CA 94117

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Email: *imiranda2@usfca.edu*

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Abstract: In the United States alone, each tropical cyclone causes an average of $14.6 billion worth of damages. In addition to the destruction of physical infrastructure, natural disasters also negatively impact human capital formation. These losses are often more difficult to observe, and therefore, are over looked when quantifying the true costs of natural disasters. One particular effect is an increase in infant mortality rates, an important indicator of a country's general socioeconomic level. This paper utilizes a model created by Anttila-Hughes and Hsiang, that takes advantage of annual variation in tropical cyclones using annual spatial average maximum wind speeds and Demographic and Health Surveys data, in order to find a causal relationship between infant mortality and tropical cyclones. The results show that there is a statistically significant increase in infant mortality with a lagged effect. This research topic is even more relevant given the evidence on climate change such as rising sea temperatures, which aggravates both the occurrence and severity of tropical cyclones.

Key words: Tropical cyclones; Weather variability; Infant mortality; Indirect effects; Development

1. Introduction

The National Oceanic and Atmospheric Administration (NOAA) defines a tropical storm as a rotating low-pressure system that originates in tropical waters with winds of at least 74mph. These natural disasters have approximately affected 466.1 million individuals in a 30-year period between 1977 and 2009 (Doocy, Dick & Daniels, 2013). This number will only continue to rise as coastal populations increase and climate change unfolds. While quantifying the number of people impacted by tropical cyclones is very important, deciphering how and when individuals are impacted is crucial to developing policies that mitigate disaster damages. This study aims to find a causal link between infant mortality and lagged exposure to tropical cyclones, and quantify the magnitude of these time-lagged effects relative to immediate ones.

The first part of studying natural disasters, such as tropical cyclones, is breaking down their impacts into direct and indirect effects. Direct damages are those that occur at the time the disaster hit and include destruction of physical assets like buildings, roads, equipment, and crops, as well as direct loss of life. These damages are the easiest to observe and therefore, are usually the ones studied and quantified when accounting for the cost of a disaster. Indirect damage refers to goods and services that will not be produced after the disaster has hit as a result of direct damages, as well as impacts to human capital such as health and education (ECLAC, 2003). The first problem when trying to quantify the true total costs of natural disasters is measuring the indirect impacts, because they are incurred after a disaster has hit and can endure long after. Consequently, these impacts are harder to observe and quantify, which often leads to miscalculations when reporting the costs and effects of a disaster.

Developing countries located in the tropics face a higher risk from tropical cyclones due both to their geographical location (i.e., located at latitudes with warmer sea temperatures) and economic circumstances, and accordingly, it is worth noting the importance of advancing further research in these countries. Moreover, because these countries find themselves in hazard-prone areas, their economic development is constantly slowed due to increased public expenditure on disaster relief, lower revenues from reduced economic activity and any losses incurred by the tropical storm (Pelling, Özerdem & Barakat, 2005). The previously mentioned problems involving correctly quantifying the true costs of natural disasters only become more difficult in the context of developing countries due to the lack of resources, standardized processes and consistent data available. A further problem when trying to estimate the true costs and impacts of natural disasters is measuring the long-term economic and social effects. In particular, consequences on human capital, including negative effects on health, nutrition and education, which have been found to be both large and long-standing, are difficult to accurately measure (Baez, de la Fuente, Santos & Vanessa, 2010).

This paper addresses some of these issues by specifically focusing on indirect damages to human capital in developing countries by measuring the post-disaster infant mortality effects of tropical cyclones. Due to the random occurrence of tropical cyclones, I am able to apply quasi-experimental techniques to identify their effect on infant mortality using tropical cyclone data with the cross-sectional household-level Demographic and Health Survey (DHS). Through various analyses, I find that tropical cyclones have a significant and lagged impact on infant mortality. Furthermore, these lagged impacts are larger in magnitude than the initial effect of the disaster. The remainder of the paper first describes the literature of economic outcomes and natural disasters. Secondly, outlines the data sources and methodology I will be using to establish a causal effect between tropical cyclones and infant mortality. Then I present the data analysis of my results, and lastly, I offer a conclusion and some policy recommendations.

2. Literature Review

For some time now, researchers have studied and estimated the effects of natural events on humans. While we may not be able to change or control the environment, knowing the impacts they have on humans and economics is useful for designing and implementing policies. In particular, as climate change becomes a more pressing concern, investigating the effects of natural events is even more relevant. First, I will describe the literature discussing methodologies for studying the climate and its impacts. Second, I will review the theory and empirics behind natural disasters, human capital investment and consumption smoothing. Third, I will present studies specifically looking at the importance between infant mortality rates and natural disasters. Lastly, I will focus on the evidence revealing that shocks are particularly disruptive to the wellbeing of females, relative to males.

A key advantage of climate and weather shocks is that they have a varying and exogenous effect over time within regions, allowing for a more clean identification strategy to measure a variety of different economic outcomes. Estimating outcomes using different climate variables can be done a number of ways. The classical approach to measuring weather shocks is using spatial variation for a fixed point in time; however, this simple model can suffer from omitted variable bias from the correlation between climate variables and outcomes (Dell, Jones & Olken, 2014). Panel datasets only strengthen the identification strategy of the classical model, by including fixed effects for different regions. The model is then able to absorb any possible omitted variable bias that the simple classical approach suffers from, and the results are then able to illuminate the effects of the climatic event (Carleton & Hsiang, 2016). In this study, I will be using this more advanced model derived from panel datasets to observe the effects of weather shocks (tropical cyclones), focusing on the variation in time within a given region. By including fixed effects for different regions the model will absorb any possible omitted variable bias that the simple classical approach suffers from. Despite its advantages, panel data estimation techniques are still limited in their ability to predict long-run effects and adaptation to climate change. Reasons for the limitation in the model include lack of predictability for adaptation, intensification of climate effects, and general equilibrium effects, all of which highlight that panel models can identify a causal effect of climate shocks, but cannot accurately predict nonlinearities, displacement, uncertainty or adaptation of climate shocks (Hsiang, 2016) (Dell, Jones & Olken, 2014). One-way to improve the panel data set classical approach model is to incorporate a lag that is interacted with the weather effect. This distributed-lag model builds on the panel data model by allowing the effects of different independent factors on a dependent variable to occur over time, as well as describe the time structure of the effect (Gasparrini, Armstrong & Kenward, 2010). The model also assumes additive separability between delayed impacts, which resolves the problem that additional responses to weather shocks that are incurred later may not only be due to that specific event (Hsiang, 2016). This is particularly important in the case of this study because climate impacts are known to reveal their impacts over time, and consequently require a dynamic model that shows this relationship.

Using these more developed econometric models, researchers are now able to better isolate the indirect and long-term impacts of natural disasters. The first and easiest observable impact of natural disasters on human capital is loss of life; evidently, death reduces the amount of human capital, which is typically well quantified. The second indirect impact is the decrease of household income, which results in reallocation of resources. These secondary effects, related to the economic conditions and fractured infrastructure left behind after the natural disaster, also include slow economic growth, increased debt and fall in production (Baez & Santos, 2007). This study primarily focuses on the indirect impacts of natural disasters, which affects human capital in the long run by destabilizing household consumption expenditures such as food, health or education when a shock occurs (Baez et al., 2010). Consumption smoothing theory is built on evidence from numerous empirical studies, which revealed that natural disasters decrease household investment, specifically in children's human capital, in order to smooth household consumption and mitigate risk (Udry, 1994) (Jensen, 2000). Non-equilibrium dynamic models have been developed to show how constraints to income in the short-run, as a result of shocks, can create poverty traps and slower long-term growth rates in the future (Van den Berg, 2010). Investing in education and health, while being good investments with high returns, are not the typical kinds of investments that households will make, according to consumption smoothing theory and non-equilibrium models. This might explain the lagged effects of tropical cyclones on infant mortality.

Studies have looked at how decreases in household income result in children weighing less and experiencing stunted growth, which can have adverse economic and health outcomes later on in life (Buser, Oosterbeek, Plug, Ponce & Rosero, 2016). Evidence shows that natural disasters may decrease household investment specifically in children's human capital by reallocating their time previously devoted to school towards the labor market in order to smooth consumption (Skoufias, 2003). This result is consistent across various countries. A study conducted in the Philippines revealed that typhoons reduce household income by 6.6%, which led to a significant decline in human capital investments in education by 13.3% and in medical expenditures by 14.3% (Anttila-Hughes & Hsiang, 2013). Another study performed in Indonesia found that women's wellbeing is highly correlated to the environmental conditions they experienced in early life; finding that rainfall has a positive impact on agricultural output, which then increases household expenditure on girl's health and schooling (Maccini & Yang, 2009). Another study done in Colombia investigated the effects on children's nutrition and schooling following the 1999 Armenia earthquake both in the short and medium term, and found negative effects (Bustelo, Arends-Kuenning & Lucchetti, 2012). Similarly, a study in Zimbabwe examined the effects of shocks such as droughts, showing that early life malnutrition is correlated with decreased stature as a young adult and fewer completed years of school (Alerman, Hoddinott & Kinsey, 2006). Natural disasters also have numerous public health implications. Epidemiologic evidence, the branch of medicine dealing with the incidence rates of diseases, points out that natural disasters, particularly floods can increase disease incidence rates through poor water and sanitation supplies, in turn affecting human health (Ahern, Kovats, Wilkinson, Few & Matthies, 2005). For example, one study found that heavy rainfall is associated with an increase in outbreaks of bacteria that infects intestines, usually as a result of a contamination of water supplies. This can have lasting impacts on individuals, especially children. (Kovats, Bouma, Hajat, Worrall & Haines, 2003). While natural disasters impact human capital to individuals of all ages, those who are impacted in the early stages of life can have serious consequences such as poor health, causing lower school performance and slower cognitive development and ultimately impact future earnings and productivity (Baez et al., 2010).

Infant mortality rates are considered to be an accurate indicator of the general socioeconomic level of a country, and as such, many researchers have looked specifically at how natural disasters affects infant mortality rates (Brenner, 1973). The fetal origin hypothesis, which originates from the epidemiologist David Baker, suggests that environmental conditions before and shortly after birth have significant impacts on wellbeing outcomes later on in life (Almond & Currie, 2011) (Baker, 1995) (Heckman, 2007). Numerous studies have researched the impact of GDP shocks to early life mortality. A study conducted across 59 developing countries showed that there is a strong negative correlation in the short run between GDP per capita and infant mortality, particularly amongst female infants (Baird, Friedman, and Schady, 2011). Another cross-national study in developing countries found similar results, revealing that reductions in GDP per capita correlate with a significant rise in mortality for children under the age of 5 (Pérez-Moreno, Balnco-Arana & Bárcena-Martín, 2016). Similar results were found in the United States, a developed country, showing an inverse relationship between economic changes, such as unemployment rates and infant mortality (Brenner, 1973). This study also specifically looked at differential lags of infant mortality, which is pertinent to my project, and found approximately a one-year lag in the increase of infant mortality proceeding negative shocks to the economy (Brenner, 1973).

These negative shocks, both economic and weather related, have been found to be notably damaging to girls. Assuming that economic development theory is true that better economic conditions improve women's wellbeing and reduces poverty in communities, then the reverse must also be true. When economic conditions are worsened, whether that may be due to natural disasters or not, women's outcomes are worse than men's. Different theories have attributed this to biological and physical differences between women and men as well as to differing vulnerabilities influenced by social norms (Neumayer & Plümper, 2007). Empirically, these theories seem to hold as well. In Sub-Saharan Africa, droughts were found to significantly affect female infant mortality more than male, with 12 more infant girl deaths per 1,000 births than infant boy deaths (Flato & Kotsadam, 2015).

Similarly, in the Philippines infant mortality amongst females was measured to be 15.1 times larger than initially reported (Anttila-Hughes & Hsiang, 2013). Overall, the literature shows how sensitive early life mortality rates are to negative shocks, even if they do not occur immediately. A limitation of the fetal origin theory, however, is whether or not the links between early life health investments or shocks have a causal link to economic outcomes later in life. This is mainly due to the econometric challenges of identifying long-term effects.

The body of literature in this field has made significant progress in the theory and empirics of modeling causal relationships between climatic events and economic outcomes and documenting the effect of children's wellbeing as a result of income shocks, in particular amongst females. However, there is still progress to me made when measuring the long-term and indirect effects of climate and analyzing these effects across countries. This research project adds to the literature by providing additional evidence on the effects and magnitude of tropical storms across multiple developing countries. Furthermore, this project highlights the indirect impact and costs of tropical storms on human capital by analyzing infant mortality rates not only in the year of the disaster but also in subsequent time-lagged periods.

3. Sample and Data Sources

3.1 Tropical Cyclone Data

My data on tropical storms is taken from the International Best Track Archive for Climate Stewardship (IBTrACS) database, which was developed by The National Oceanic and Atmospheric Administration's (NOAA) Climate Data Center. This is an extremely useful database because it contains the complete data on historical tropical storms by combining different datasets with information on storm positions, wind speeds, pressure and intensity. This historical dataset is then reconstructed with the Limited Information Cyclone Reconstruction and Integration for Climate and Economics (LICRICE) model using wind field measures (Hsiang, 2010). In order to match tropical cyclone exposure with the annual household data, the LICRICE model is summarized into a single observation (spatial average maximum wind speed) for each region each year. It's important to note that this wind speed variable is different from the actual wind speed at the center of a storm, which is much larger but not directly comparable. Using this reconstructed dataset I am able to find the number of storms that occurred in each country, as well as the average intensity of each storm (see Table 1 for more details). Figure 1 displays the interquartile distribution of tropical cyclone exposure by country, revealing that there is a large variation in exposure between countries. The annual spatial average maximum wind speed across all the countries in my sample is 11.80 meters per second.

3.2 Infant Mortality Data

I then merge the tropical cyclone data with cross-sectional data retrieved from The Demographic and Health Survey (DHS) Program. The DHS Program was founded in 1984 and attempts to capture trends in health and population across 90 developing countries with over 300 surveys. I rely primarily on the health surveys because they are conducted at the household level and have proportionate samples from each country, providing data on a variety of indicators regarding population, health and nutrition. Furthermore, since the DHS surveys are highly standardized, it allows for a clear comparison of surveys across and within countries over time. Using these cross-sectional surveys, I create a panel data for each woman starting from the time she was 15 until the date she was surveyed with information on fertility and infant mortality events, as well as the household's location in order to identify its administrative region. The sample excludes women who migrated, which minimizes endogeneity concerns of families relocating to regions with less tropical cyclone exposure. Since the DHS surveys stopped inquiring about migration in 2010, I am also excluding any surveys conducted after that year. From this women level panel data set; I am able to weave out information from each child, creating a new global child cross-section dataset. While the DHS has data for 90 countries, I am only conducting analysis on the following 12 countries: Bangladesh, Cambodia, Comoros, Dominican Republic, Honduras, Haiti, India, Madagascar, Mozambique, Nicaragua, Philippines, and Vietnam. These countries were chosen because they are a subsample of all the countries where both tropical cyclones occur and where the DHS has conducted health surveys; additionally, they have enough variation in tropical cyclone incidence to estimate results. In the global sample there are 578,384 non-migrant infants observations across nearly 11 years between 1979 and 2008.

4. Methodology

In order to answer my research question, (do tropical cyclones affect infant mortality rates after exposure to a storm, and if so, how large are these time-lagged effects relative to immediate ones), I use the strongest storm in a given year in a given region, which is determined by annual spatial average maximum wind speed, to act as my treatment. This approach was chosen because it allows the model to capture the intensity of storms while controlling for the differences in physical size of each administrative region. I argue that this treatment variable is in fact a random exogenous occurrence because the location, timing and trajectory of tropical cyclones are unpredictable and arbitrary, allowing for a clean identification strategy.

In order to properly identify the impact of tropical cyclones on infant mortality rates, the model uses a difference-in-difference econometric approach taking advantage of the random variation to tropical cyclone exposure in different regions. I rely on random yearly variations in tropical cyclone exposure within each specific region to control for cross-sectional differences in exposure to tropical cyclone intensity. This is accomplished by including a region fixed effect in the model in order to absorb any of these average cross-sectional differences in tropical cyclone exposure. I then include a country-by-year fixed effect in order to avoid spurious relationships in tropical cyclone incidence and infant mortality. This fixed effect compares each country each year to each other. Moreover, the time fixed effect takes into account any unobservable climatic trends, which might be correlated with tropical cyclone exposure and its impacts, such as El Niño years, which cause warmer water in the Pacific Ocean, aggregating tropical cyclone incidence. By using this two-way fixed effect model, I can observe what happens to infant mortality conditional on tropical cyclones exposure in a specific region in a specific year. Put differently, I am comparing within each county across regions each year from 1979-2008.

In order to estimate the effect of tropical cyclones on infant mortality, I use the linear probability model developed by Anttila-Hughes and Hsiang in their study (2013). My regression specification is the following:

$$Y_{wrct} = \sum_{L=0}^{10} (\alpha_L W_{r,t-L}) + \tau_{tc} + \mu_r + \in_{rt}$$

The dependent variable, Y, corresponds to the probability of a binary variable being either zero (probability the infant survives) or one (the probability the infant dies), which is determined by the explanatory variables. The parameter of interest α indicates the number of additional women, out of one thousand, who report their infant has died as a result of an increase in wind speed of one meter per second. The various sub-indexes in the model are: *r* for region, *w* for woman, and *t* for year. W is the spatial average maximum wind speed of a tropical cyclone in the Lth year before the infant was born. The regression uses a distributed time lag in order to measure the effects of tropical cyclone exposure for years after the storm has occurred, with lags indexed by L. I am including 10 lagged year variables in order to try and capture the long-run economic effects of tropical cyclones, which have been found to be both large and negative (Hsiang & Jina, 2014). The model also introduces a county-by-year fixed-effect, τ_{tc} as well as a region level fixed-effect, μ_r, which control for any time-invariant region and year characteristics. The variable $\in r$ represents the clustered standard errors at the region level because treatment (tropical cyclone exposure) happens at the region level. It also accounts for any serial correlation of the errors within a region. In short, the model looks at the likelihood an infant dies due to tropical cyclone exposure, which is measured by spatial average maximum wind speed (in meters per second), conditional on being non-migrant, and controlling for spatial and time fixed effects.

5. Data Analysis & Results

My analysis is divided into various sections. The first looks at the impact of tropical cyclone exposure on infant mortality, within individual countries. Then I conduct the same analysis looking at all the countries pooled together. To check the consistency of my results, I then analyze the results by various sub-regions: Latin America, Asia and Africa. Additionally, I run various robustness checks. The parameter of interest from my model, α, is interpreted as the number of additional women, out of one thousand, who report the death of an infant as a result of an increase in wind speed of one meter per second. The first column of the tables analyzes the result amongst female infants, the second column amongst male infants and the third column amongst both female and male infants together. Overall, these preliminary results indicate that there is consistent and causal relationship between infant mortality and tropical storms with a time-lagged effect. Table 1 is a summary statistics table of my treatment, tropical cyclone exposure. The table breaks down number of tropical cyclones in each country. Figure 1 graphically depicts the interquartile distribution in the variation of annual maximum wind speeds in each country. As both the table and figure reveal, the number of storms as well as the intensity of them varies drastically across countries. The spatial average maximum wind speed across all the countries in my sample is 11.80 meters per second.

5.1 Infant Mortality Within Country

The first step in my data analysis was replicating the results from Anttila-Hughes and Hsiang in the Philippines. While Anttila-Hughes and Hsiang only looked at a four-year lag, I extend my analysis to ten years after the storm to check if there is an enduring poverty effect. My within country analysis of the Philippines reinforces the results from Anttila-Hughes and Hsiang; tropical cyclone exposure does increase infant mortality, however, it only does so statistically significantly amongst females. As shown in Table 12, conditional on being female, there is a statistically significant increase in female infant mortality starting one year after a cyclone has occurred, and it endures six years after the disaster (although not significant in the fourth and fifth year). Given the spatial average wind speed of a cyclone in the Philippines, 18.69 m/s (see Table 1), for every 1,000 births, this effect corresponds to an increase of about 11 additional deaths in the first lagged year, 5 additional deaths in the second lagged year, 9 additional deaths in the third lagged year and almost 8 additional deaths in the lagged sixth year. Again these results mirror those from Anttila-Hughes and Hsiang 2013.

Other countries in my sample are not exposed to the same consistent strong tropical cyclones every year; consequently, it's difficult to find such a strong and consistent signal like in the Philippines. One country where I did find similar effects of tropical cyclone exposure was in Haiti, despite being struck with about ten times less storms and slightly lower spatial average wind speeds than the Philippines. The spatial average maximum wind speed of a tropical cyclone in Haiti is 15.99 meters per second. Table 6 shows the regression results from Haiti. Conditional on being female there is a statistically significant increase in infant mortality in the second through fourth year after a tropical cyclone has occurred. This effect corresponds to almost 11 additional deaths in the second lagged year, about 18.5 additional deaths in the third lagged year and 21 additional deaths in the fourth lagged year; each effect is per 1,000 births for an average tropical cyclone in Haiti. Interestingly, there is also a significant increase in male infant mortality much later, in the sixth and eight lagged years. These effects correspond to an increase in almost 16 and 12 additional deaths per 1,000 births for an average storm in the sixth and eighth lagged years, respectively. According to the World Bank, Haiti is the poorest country in the Western Hemisphere, and one of the poorest developing countries, which might explain why the country is so sensitive to natural disasters and more prone to lasting poverty effects.

5.2 Infant Mortality Global Trend

From the 12 individual country data sets, Bangladesh, Cambodia, Comoros, Dominican Republic, Haiti, Honduras, India, Madagascar, Mozambique, Nicaragua, The Philippines and Vietnam, I create a new global sample dataset that is reweighted by number of observation in each country. Using this global dataset I am able to analyze if there is an overarching general effect that tropical cyclones have on infant mortality (see Table 14). Conditional on being born female, there is a positive and statistically significant effect on infant mortality on the third year lag and a negative effect in the ninth year; this might be a coincidence. The coefficient on the third lagged can be interpreted as an increase in about 2 additional deaths for every 1,000 births for an average storm in my sample. Conditional on being born male, there is a statistically significant increase in infant mortality in the fourth and sixth lagged year. This corresponds to an increase in about 3 additional deaths in the fourth lagged year; and about 4.5 additional deaths in the sixth lagged year deaths for every 1,000 births for an average storm. Similarly, when analyzing both genders together, there is a significant increase in infant mortality as a result of a one meter per second increase in wind speed in the third, fourth and sixth year. These coefficients indicate an increase of about 1.65, 2.5 and 3 additional deaths for every 1,000 births for an average tropical cyclone in the third, and fourth and sixth lagged yeas respectively. For a graphical representation of these coefficients see Figures 2, 3, and 4. The conclusion from this table is that there seems to be a lagged poverty effect that is significant starting from the third year moving forward that causes an increase in infant mortality and is statistically significant. This unfortunately means that the effect of tropical cyclone exposure even prior to an infant being is conceived, statistically impacts whether he or she will live past their first birthday. One explanation why there are no significant results until the 3rd lagged year, could be that in general, governments and international organizations provide a lot of aid after a storm occurs. However, after a year or two the aid decreases, despite still being necessary, so families are more susceptible to fall into poverty traps.

I continue my analysis by generating an average eight-year lagged exposure variable. I limit the average exposure to eight years as opposed to ten, because it is during those eight years that I find that tropical cyclones have a statistically significant lagged effect on infant mortality. This is used as a robustness check to test if the average lagged exposure is greater than the effect of immediate exposure. Table 15 reveals that the indirect impact of tropical cyclone exposure is in fact larger than the effect of immediate exposure.

Only in the column that looks at male infants alone is the result not statistically significant, which makes sense according to the literature that female infants are more vulnerable to shocks. Amongst female infants we see that an eight-year average exposure causes about 15 additional deaths per 1,000 births for an average storm. Looking at both female and male together there is a slightly lower effect of about 13.5 additional deaths per 1,000 births for an average storm. Amongst females the indirect effect of tropical cyclone exposure is about 17% larger than the direct effects; this is around the same magnitude difference that Antilla-Hughes and Hsiang found in the Philippines. These results are not only consistent with previous studies, but they provide further evidence supporting my argument that tropical cyclone exposure does increase infant mortality with a lagged effect that are larger than immediate ones due to the enduring poverty effects created by natural disasters.

In order to further ensure the robustness of my results I ran my regressions with both two leads and eight lags. I chose this to keep the same amount of coefficients, highlight the eight-year lagged exposure where I find most of my results, and still check that there is no effect before the storm occurs. Table 16 displays the results from the pooled global sample. In all three columns none of the leads are statistically significant, like they should be. Furthermore, we see that female infant mortality is consistently significant in the lagged coefficients starting with the second lagged year, then the third and finally the sixth. Amongst males the effect is not significant until the fourth lagged year but it is again also significant in the sixth lagged year. The pooled results from both genders in column three are very similar to the initial regression results showing a consistent effect beginning in the third lagged year, and popping up in the fourth and sixth lagged year as well. Additionally, also mirrors the results from Antilla-Hughes and Hsiang 2013, thus providing further evidence on the stability and robustness of my results. These results are also graphically represented in Figures 6, 7, and 8.

5.3 Infant Mortality Sub-Regions

In addition to looking at the global sample I checked the results by sub-regions, Latin America, Asia and Africa, to see if there was a consistent effect. The Latin American sub-region incorporates Dominican Republic, Haiti, Honduras and Nicaragua. The Asian sub-region contains Bangladesh, Cambodia, India, The Philippines and Vietnam. Lastly, the African sub-region includes Comoros, Madagascar and Mozambique.

Table 17 displays the results of an increase in wind speed in meters per second on infant mortality in Latin America. An average storm in this region has a spatial average maximum wind speed of 12.49 meters per second. Conditional on being female, I found a similar result as the global regression with a positive and significant impact in the third and fourth lagged year. These coefficients correspond to an increase in about 7.5 additional deaths three years after the storm and about 7 additional deaths four years after the storm for every 1,000 births for an average storm. Conditional on being male, there are a couple of negative coefficients, although not significant, which could indicate the gender preferential of males and households reallocating resources from females to males when a shock occurs. There is a statistically significant increase in male infant mortality of almost 7 additional deaths for every 1,000 births for an average storm in the sixth year after a cyclone has struck. When looking at both genders pooled together, the third and sixth year lagged have a statistically significant coefficient. The ninth year lag is also significant, but negative, which could potentially mean that the region is recovering from the poverty effect caused by the tropical cyclone.

The results from the sub-region of Asia are quite interesting, as noted by Table 18. Most of the coefficients are in fact negative and not significant. I hypothesize this could be due to the fact that both India and Bangladesh are such large countries, in terms of populations, and have quite low tropical cyclone exposure; therefore, it's swaying the results. I ran the same analysis excluding both these countries and limiting it to Cambodia, the Philippines and Vietnam, essentially South-East Asia, and found results that were similar to both the global analysis and to the Latin-American sub-region (see Table 19). Amongst these countries, the spatial average maximum wind speed of a typical tropical cyclone was 12.05 meters per second. Conditional on being female, infant mortality increases significantly one year after the storm, which can be interpreted to about an additional 5 deaths per 1,000 births for an average storm. This is a similar effect to the one found by Anttila-Hughes and Hsiang. Conditional on being male, the coefficients are mainly negative; two years after a storm there is a significant increase in about 3.5 births per 1,000 births. Again, this could be due to a strong son preference in Asia.

Lastly, Table 20 presents the impacts of tropical cyclone in the sub-region of Africa. The spatial average tropical cyclone wind speed in Africa is 10.64 meters per second, the lowest of any of my sub-region and global analysis. In contrast to Latin America and Asia, I find that there is a consistent increase in male infant mortality that is statistically significant in the fourth, fifth and seventh lagged years. These coefficients correspond to approximately an additional 6, 5.5 and 5.5 deaths per 1,000 births for an average storm. Amongst females, there is only a statistically significant increase in infant mortality in the seventh lagged year, and this is also true for when I look at the results of both genders together.

Overall, the sub-regions parallel the global results, revealing that tropical cyclones have a lagged impact on infant mortality. The mechanism, by which this happens, I believe, is through a poverty effect that is incurred after a storm occurs and endures long after. Given the evidence from Hsiang and Jina 2014, that tropical cyclones have significant negative economic impacts that longstanding, my results and poverty effect explanation seem to be accurate.

6. Conclusions and Implications

Using historical tropical cyclone data and household surveys from the DHS I show that tropical cyclones do have a significant lagged impact on infant mortality, and that this effect is larger in magnitude relative to the immediate impact of tropical cyclone exposure. Across all my analysis, the lagged impacts become significant usually as of the third lagged year; this could possibly be explained by the fact that both governments and NGO's provide a lot of relief aid recently after the occurrence of a natural disaster, and as more time passes aid decreases, allowing the emergence of the poverty effect. This poverty effect is the mechanism through which infant mortality increases. The results from this project also imply that tropical cyclones have significant negative indirect consequences, which are not currently being taken into consideration when quantifying and reporting the costs of a tropical cyclone. Given the extensive literature on the importance of early life human capital formation, these results have serious implications for economic development.

Infant mortality rates are an important indicator of socioeconomic wellbeing. The repeated exposure to tropical cyclones implies infants are affected by these conditions that lowers their probability of survival, and even if they do survive they will be worse off. As a result of the high infant mortality rates, developing countries will have slower human capital growth rates, which from both theoretical and empirical models, we know is crucial for sustained economic growth. If the cause of these lagged deaths is a poverty effect as a result of the tropical cyclone, then governments need to design better disaster aid policies. These policies must not only provide relief at the time of disaster to mitigate direct costs and loss of life, but also long-run relief to alleviate any indirect burden households might have as a result of tropical cyclone exposure, such as reduced household income and resources. These indirect burdens that can endure long after a disaster occurs can increase the probability that an infant dies before her or his first birthday, and therefore should be a primary focus for policies.

The results I presented were interpreted for the spatial average tropical cyclone wind speed. Given the evidence of climate change, the spatial average wind speed of tropical cyclone is only likely to keep increasing, magnifying the presented results exponentially. Based on this study, it would be my policy recommendation that governments not only enact policies to mitigate the effects of climate change, but also take measures to adapt society to these new changes in order to limit the damages of tropical cyclones and other disasters. I also would recommend that further research be done to find out the specific mechanisms that cause infant mortality to increase, as well as other research on the indirect impacts of tropical cyclones in order to raise more awareness of the costs of disasters and climate change.

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Appendices

Table 1: Tropical Cyclone Exposure (Maximum Wind Speed) Summary Statistics.

Country	Years	N	Mean	Std. Dev.	Min	Max
Bangladesh	1979-2008	58	12.67	9.04	0.13	40.59
Cambodia	1979-2007	93	7.33	5.92	0.03	22.56
Comoros	1979-1997	15	13.52	7.58	0.92	27.59
Dominican Republic	1979-2008	51	16.96	12.31	0.09	61.01
Haiti	1979-2007	40	15.99	12.03	0.31	53.58
Honduras	1979-2007	54	9.14	9.33	0	42.16
India	1979-2007	123	10.97	6.91	0.07	35.05
Madagascar	1979-2008	137	9.78	7.82	0.02	28.73
Mozambique	1979-2005	54	8.64	6.98	0.03	26.79
Nicaragua	1979-2002	29	7.88	8.51	0.21	40.28
Philippines	1979-2008	411	18.69	11.62	0.02	53.47
Vietnam	1950-2003	212	10.13	6.41	0	26.56

Notes: Maximum wind speed measured in meters per second

Figure 1: Tropical Cyclones Exposure Across the World

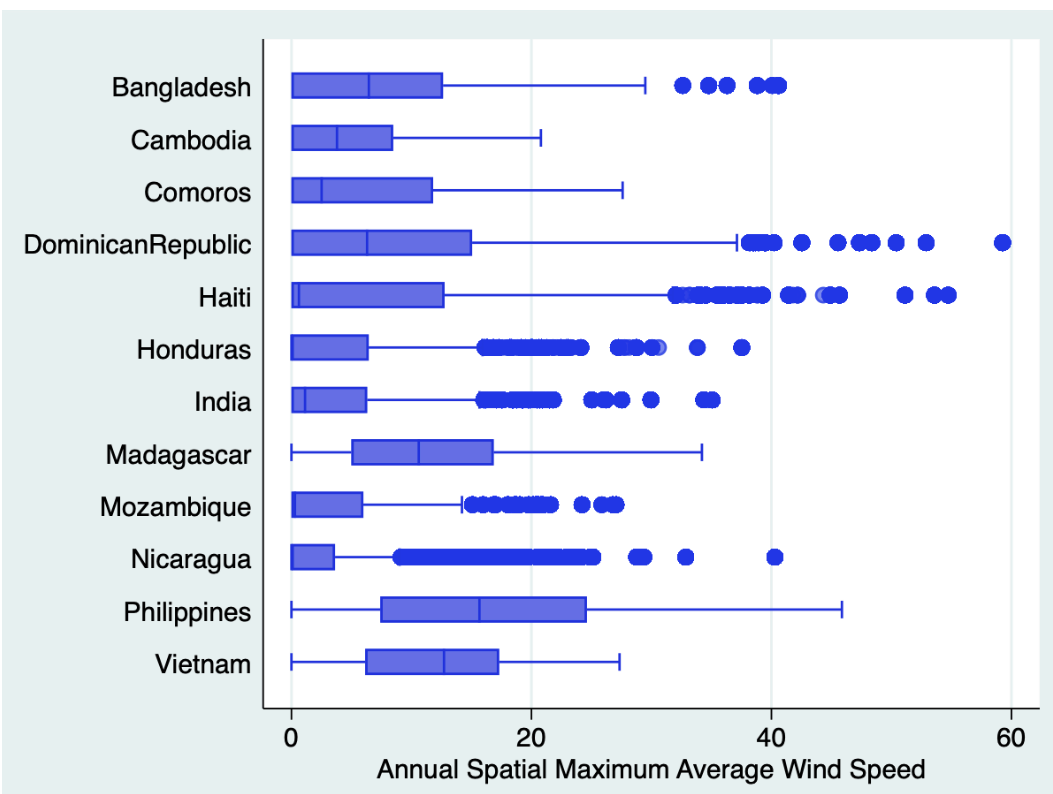

Figure 1: Box-whisker plot of the distribution in national annual maximum wind speed measure.

Table 2: Impact of Tropical Cyclone Exposure in Bangladesh

	(1)	(2)	(3)
VARIABLES	Female	Male	Both
Max wind speed	0.400	-0.340	0.0315
	(0.415)	(0.870)	(0.468)
L1_max wind speed	-0.825**	-0.0485	-0.428
	(0.316)	(0.701)	(0.383)
L2_max wind speed	0.878*	0.173	0.553**
	(0.431)	(0.124)	(0.192)
L3_max wind speed	-0.639	-0.247	-0.409
	(0.487)	(0.790)	(0.590)
L4_max wind speed	-0.0710	0.686	0.332
	(0.534)	(0.429)	(0.417)
L5_max wind speed	-0.208	0.984**	0.376*
	(0.474)	(0.290)	(0.182)
L6_max wind speed	-0.345	-0.605	-0.457
	(0.291)	(0.325)	(0.262)
L7_max wind speed	-0.0952	0.743	0.341
	(0.233)	(0.427)	(0.184)
L8_max wind speed	-0.742	0.211	-0.240
	(0.449)	(0.345)	(0.172)
L9_max wind speed	-0.477	0.958	0.247
	(0.506)	(0.504)	(0.446)
L10_max wind speed	-0.634	-0.873	-0.776*
	(0.705)	(0.541)	(0.381)
Constant	80.08***	58.30***	68.27***
	(9.932)	(10.17)	(7.026)
Observations	12,459	12,931	25,390
R-squared	0.034	0.038	0.034

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Impact of Tropical Cyclone Exposure in Cambodia

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	-0.137	-0.249	-0.168
	(0.450)	(0.673)	(0.455)
L1_max wind speed	1.087*	-0.211	0.436
	(0.548)	(0.622)	(0.388)
L2_max wind speed	0.0129	0.558	0.287
	(0.893)	(0.693)	(0.558)
L3_max wind speed	0.00679	0.0816	0.0585
	(0.550)	(0.408)	(0.354)
L4_max wind speed	-0.344	-0.00645	-0.155
	(0.714)	(0.746)	(0.505)
L5_max wind speed	-0.201	-0.648	-0.410
	(0.977)	(1.094)	(0.795)
L6_max wind speed	1.122	0.275	0.713
	(0.953)	(0.979)	(0.707)
L7_max wind speed	-0.667	0.383	-0.0957
	(0.858)	(0.519)	(0.568)
L8_max wind speed	0.941	0.177	0.595
	(0.704)	(0.767)	(0.507)
L9_max wind speed	0.734	1.632*	1.215**
	(0.515)	(0.846)	(0.553)
L10_max wind speed	1.271*	1.351	1.318
	(0.708)	(1.060)	(0.833)
Constant	57.09**	74.22***	64.75***
	(23.81)	(20.96)	(19.49)
Observations	21,075	21,917	42,995
R-squared	0.029	0.028	0.027

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Impact of Tropical Cyclone Exposure in Comoros

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	2.334***	0.832	1.596*
	(0.102)	(0.892)	(0.434)
L1_max wind speed	-0.873	-0.130	-0.523
	(0.345)	(0.104)	(0.191)
L2_max wind speed	3.766***	0.837	2.151**
	(0.367)	(0.601)	(0.357)
L3_max wind speed	-1.285	1.043	-0.0547
	(0.469)	(1.304)	(0.851)
L4_max wind speed	1.110	0.207	0.706
	(0.706)	(1.274)	(0.968)
L5_max wind speed	0.706**	0.981	0.729
	(0.0939)	(0.404)	(0.293)
L6_max wind speed	0.536	3.900*	2.116*
	(0.348)	(1.055)	(0.664)
L7_max wind speed	0.198	-0.904*	-0.517**
	(0.115)	(0.213)	(0.0942)
L8_max wind speed	3.966***	-0.268	1.718***
	(0.212)	(0.633)	(0.125)
L9_max wind speed	-3.780**	3.428	-0.144
	(0.513)	(2.082)	(1.203)
L10_max wind speed	0.561	-0.298	0.00909
	(0.371)	(2.714)	(1.169)
Constant	11.18*	10.29	14.15
	(3.421)	(10.31)	(5.111)
Observations	3,065	3,023	6,088
R-squared	0.042	0.039	0.036

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Impact of Tropical Cyclone Exposure in the Dominican Republic

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	0.388**	0.182	0.286***
	(0.155)	(0.222)	(0.0773)
L1_max wind speed	0.206	0.0524	0.130
	(0.303)	(0.232)	(0.236)
L2_max wind speed	0.0740	0.273*	0.175*
	(0.146)	(0.124)	(0.0792)
L3_max wind speed	0.0951	0.332	0.218
	(0.0923)	(0.238)	(0.157)
L4_max wind speed	-0.00681	0.252	0.118
	(0.146)	(0.146)	(0.0917)
L5_max wind speed	0.111	0.284	0.200
	(0.225)	(0.187)	(0.176)
L6_max wind speed	0.154	0.158	0.154
	(0.268)	(0.192)	(0.199)
L7_max wind speed	0.189	-0.0100	0.0877
	(0.127)	(0.164)	(0.0858)
L8_max wind speed	-0.104	-0.296	-0.201
	(0.116)	(0.166)	(0.126)
L9_max wind speed	-0.149	-0.337	-0.238
	(0.172)	(0.188)	(0.157)
L10_max wind speed	-0.394**	0.0597	-0.160*
	(0.167)	(0.123)	(0.0832)
Constant	21.23*	21.17**	21.12**
	(10.01)	(6.482)	(6.344)
Observations	38,280	40,003	78,283
R-squared	0.011	0.012	0.011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Impact of Tropical Cyclone Exposure in Haiti

	(1)	(2)	(3)
VARIABLES	Female	Male	Both
Max wind speed	-0.00144	-0.227	-0.138
	(0.238)	(0.312)	(0.199)
L1_max wind speed	0.400	-0.239	0.0692
	(0.471)	(0.441)	(0.446)
L2_max wind speed	0.687**	0.175	0.436
	(0.282)	(0.345)	(0.257)
L3_max wind speed	1.159***	0.536	0.838***
	(0.239)	(0.318)	(0.240)
L4_max wind speed	1.318**	0.274	0.777
	(0.451)	(0.606)	(0.426)
L5_max wind speed	0.198	-0.312	-0.0446
	(0.251)	(0.487)	(0.324)
L6_max wind speed	0.559	0.999**	0.788**
	(0.326)	(0.400)	(0.281)
L7_max wind speed	-0.0639	0.396	0.154
	(0.225)	(0.314)	(0.177)
L8_max wind speed	0.199	0.738*	0.472**
	(0.248)	(0.380)	(0.203)
L9_max wind speed	0.238	-0.384	-0.0826
	(0.266)	(0.397)	(0.268)
L10_max wind speed	0.376	-0.217	0.0744
	(0.254)	(0.759)	(0.465)
Constant	23.54**	62.13*	43.39**
	(10.15)	(28.24)	(18.44)
Observations	17,285	17,830	35,115
R-squared	0.022	0.026	0.023

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Impact of Tropical Cyclone Exposure in Honduras

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	-0.297	0.409	0.0837
	(0.617)	(0.567)	(0.429)
L1_max wind speed	-0.377	-0.411	-0.398
	(0.592)	(0.603)	(0.464)
L2_max wind speed	-0.707	0.336	-0.187
	(0.474)	(0.305)	(0.179)
L3_max wind speed	0.708	-0.245	0.228
	(0.583)	(0.186)	(0.307)
L4_max wind speed	-0.420	-0.537	-0.490*
	(0.488)	(0.362)	(0.261)
L5_max wind speed	0.416	0.871	0.659
	(0.513)	(0.692)	(0.427)
L6_max wind speed	-0.629	0.304	-0.145
	(0.741)	(0.626)	(0.282)
L7_max wind speed	1.455**	-1.012*	0.216
	(0.554)	(0.476)	(0.265)
L8_max wind speed	-0.179	-0.0467	-0.101
	(0.581)	(0.470)	(0.220)
L9_max wind speed	-1.461***	0.897**	-0.244
	(0.471)	(0.353)	(0.326)
L10_max wind speed	0.396	0.405	0.406
	(0.393)	(0.686)	(0.367)
Constant	36.02***	32.19***	33.81***
	(10.03)	(5.119)	(4.396)
Observations	8,837	9,267	18,105
R-squared	0.011	0.014	0.009

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Impact of Tropical Cyclone Exposure in India

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	-0.247	-0.118	-0.183
	(0.164)	(0.229)	(0.146)
L1_max wind speed	-0.292	-0.249	-0.264
	(0.191)	(0.289)	(0.221)
L2_max wind speed	0.0177	-0.000197	0.0113
	(0.183)	(0.239)	(0.156)
L3_max wind speed	0.0655	0.00236	0.0279
	(0.236)	(0.173)	(0.124)
L4_max wind speed	-0.155	-0.107	-0.136
	(0.201)	(0.196)	(0.154)
L5_max wind speed	-0.0420	-0.146	-0.0992
	(0.149)	(0.199)	(0.147)
L6_max wind speed	-0.172	0.0171	-0.0812
	(0.210)	(0.199)	(0.137)
L7_max wind speed	0.199	-0.0819	0.0601
	(0.216)	(0.262)	(0.202)
L8_max wind speed	-0.328	-0.122	-0.224
	(0.245)	(0.232)	(0.181)
L9_max wind speed	0.242	-0.109	0.0593
	(0.240)	(0.158)	(0.162)
L10_max wind speed	-0.362*	-0.264	-0.318
	(0.184)	(0.308)	(0.198)
Constant	41.22***	49.06***	45.31***
	(3.164)	(3.544)	(2.786)
Observations	60,680	64,372	125,052
R-squared	0.021	0.024	0.022

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Impact of Tropical Cyclone Exposure in Madagascar

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	-0.334	-0.540	-0.444
	(0.267)	(0.384)	(0.291)
L1_max wind speed	-0.779	-0.446	-0.600
	(0.397)	(0.313)	(0.308)
L2_max wind speed	-0.561	-0.643	-0.607
	(0.370)	(0.421)	(0.337)
L3_max wind speed	-0.567	-0.184	-0.369
	(0.410)	(0.282)	(0.305)
L4_max wind speed	-0.613*	0.0859	-0.254
	(0.265)	(0.280)	(0.192)
L5_max wind speed	-0.471*	0.273	-0.0910
	(0.202)	(0.325)	(0.124)
L6_max wind speed	-0.259	-0.0552	-0.166
	(0.314)	(0.226)	(0.255)
L7_max wind speed	-0.271	0.285	0.00148
	(0.245)	(0.299)	(0.0983)
L8_max wind speed	0.403	-0.178	0.110
	(0.371)	(0.340)	(0.254)
L9_max wind speed	0.0686	-0.500***	-0.236**
	(0.0786)	(0.112)	(0.0781)
L10_max wind speed	-0.0676	0.318	0.135
	(0.283)	(0.176)	(0.142)
Constant	92.21***	81.31**	86.87***
	(15.39)	(23.44)	(16.76)
Observations	27,262	28,510	55,772
R-squared	0.019	0.021	0.019

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Impact of Tropical Cyclone Exposure in Mozambique

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	0.498	0.818	0.638
	(0.503)	(0.507)	(0.417)
L1_max wind speed	0.537	0.205	0.352
	(0.498)	(0.637)	(0.411)
L2_max wind speed	0.487	-0.215	0.155
	(0.407)	(0.772)	(0.441)
L3_max wind speed	-0.211	0.320	0.0651
	(0.314)	(0.585)	(0.344)
L4_max wind speed	-0.195	0.128	-0.0282
	(0.455)	(0.458)	(0.371)
L5_max wind speed	-0.0399	0.133	0.0437
	(0.381)	(0.661)	(0.422)
L6_max wind speed	-0.0117	-1.223*	-0.631
	(0.300)	(0.601)	(0.358)
L7_max wind speed	0.215	0.532	0.374
	(0.286)	(0.537)	(0.332)
L8_max wind speed	0.0911	-0.726	-0.355
	(0.607)	(0.589)	(0.508)
L9_max wind speed	-0.573	0.514	-0.0229
	(0.492)	(0.530)	(0.315)
L10_max wind speed	1.223**	0.711	0.968*
	(0.533)	(0.626)	(0.449)
Constant	96.13***	110.8***	103.6***
	(7.747)	(7.767)	(6.809)
Observations	17,019	16,973	33,992
R-squared	0.041	0.043	0.041

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Impact of Tropical Cyclone Exposure in Nicaragua

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	0.473	-0.638	-0.108
	(0.604)	(0.676)	(0.431)
L1_max wind speed	-0.0137	0.580	0.272
	(0.516)	(0.470)	(0.373)
L2_max wind speed	0.511	-0.350	0.0534
	(0.810)	(0.644)	(0.559)
L3_max wind speed	1.050*	-0.0394	0.487*
	(0.520)	(0.484)	(0.233)
L4_max wind speed	0.127	-1.179***	-0.533
	(0.594)	(0.395)	(0.356)
L5_max wind speed	0.211	0.459	0.333
	(0.475)	(0.574)	(0.414)
L6_max wind speed	-0.0512	-0.405	-0.257
	(0.509)	(0.501)	(0.401)
L7_max wind speed	1.743**	-0.595	0.547
	(0.672)	(0.428)	(0.451)
L8_max wind speed	-0.340	-0.0815	-0.184
	(0.606)	(0.582)	(0.398)
L9_max wind speed	0.124	-0.0963	0.00188
	(0.708)	(0.636)	(0.588)
L10_max wind speed	-0.644	0.0178	-0.335
	(1.075)	(0.936)	(0.959)
Constant	18.54***	43.81***	31.70***
	(5.411)	(6.443)	(4.681)
Observations	19,317	19,873	39,190
R-squared	0.016	0.018	0.015

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Impact of Tropical Cyclone Exposure in the Philippines

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	0.314	-0.0287	0.124
	(0.209)	(0.258)	(0.103)
L1_max wind speed	0.599**	-0.172	0.191
	(0.230)	(0.202)	(0.159)
L2_max wind speed	0.284*	-0.229	0.0146
	(0.135)	(0.217)	(0.116)
L3_max wind speed	0.496*	-0.235	0.121
	(0.252)	(0.177)	(0.139)
L4_max wind speed	0.180	0.221	0.206
	(0.229)	(0.233)	(0.182)
L5_max wind speed	0.232	0.000938	0.111
	(0.174)	(0.204)	(0.123)
L6_max wind speed	0.407*	-0.0156	0.191
	(0.195)	(0.155)	(0.147)
L7_max wind speed	-0.236	0.244	0.0175
	(0.325)	(0.165)	(0.196)
L8_max wind speed	-0.113	0.327	0.119
	(0.183)	(0.221)	(0.148)
L9_max wind speed	-0.178*	0.398**	0.110
	(0.0850)	(0.155)	(0.0847)
L10_max wind speed	-0.0196	-0.319*	-0.179**
	(0.120)	(0.155)	(0.0806)
Constant	-8.675	27.29**	10.22
	(17.24)	(9.602)	(10.60)
Observations	23,670	25,222	48,892
R-squared	0.015	0.017	0.014

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Impact of Tropical Cyclone Exposure in Vietnam

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	-0.436	-0.247	-0.338
	(0.326)	(0.314)	(0.230)
L1_max wind speed	0.158	0.384	0.312
	(0.446)	(0.336)	(0.216)
L2_max wind speed	-0.268*	-0.187	-0.226
	(0.127)	(0.565)	(0.287)
L3_max wind speed	-0.0154	-0.469	-0.238
	(0.263)	(0.382)	(0.247)
L4_max wind speed	-0.280	0.0194	-0.135
	(0.171)	(0.226)	(0.169)
L5_max wind speed	-0.583	-0.489	-0.500
	(0.404)	(0.273)	(0.275)
L6_max wind speed	-0.219	-0.00658	-0.120
	(0.191)	(0.306)	(0.110)
L7_max wind speed	0.360*	0.104	0.210
	(0.175)	(0.613)	(0.285)
L8_max wind speed	0.244	0.800	0.531
	(0.412)	(0.632)	(0.274)
L9_max wind speed	-0.685	-0.0317	-0.368**
	(0.392)	(0.372)	(0.114)
L10_max wind speed	-0.301	0.900**	0.294
	(0.329)	(0.362)	(0.286)
Constant	43.69**	19.25	30.92**
	(14.58)	(26.43)	(9.698)
Observations	7,545	8,085	15,630
R-squared	0.017	0.015	0.013

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Global Impact of Tropical Cyclone Exposure

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	0.169	-0.124	0.0196
	(0.152)	(0.122)	(0.107)
L1_max wind speed	0.196	-0.0673	0.0663
	(0.144)	(0.129)	(0.114)
L2_max wind speed	0.235	-0.0171	0.112
	(0.147)	(0.161)	(0.136)
L3_max wind speed	0.180*	0.0826	0.140*
	(0.102)	(0.110)	(0.0779)
L4_max wind speed	0.149	0.284**	0.217*
	(0.142)	(0.133)	(0.113)
L5_max wind speed	-0.114	0.139	0.0169
	(0.110)	(0.157)	(0.106)
L6_max wind speed	0.167	0.389*	0.271**
	(0.108)	(0.223)	(0.130)
L7_max wind speed	0.175	0.176	0.155
	(0.143)	(0.152)	(0.110)
L8_max wind speed	0.137	0.170	0.146
	(0.155)	(0.171)	(0.117)
L9_max wind speed	-0.327***	0.0967	-0.117
	(0.116)	(0.177)	(0.0939)
L10_max wind speed	0.00557	0.164	0.0917
	(0.130)	(0.202)	(0.128)
Constant	42.15***	49.22***	45.87***
	(5.816)	(6.853)	(5.403)
Observations	256,494	268,006	524,504
R-squared	0.039	0.041	0.039

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 2: Coefficient Plot of Tropical Cyclone Exposure and Female Infant Mortality

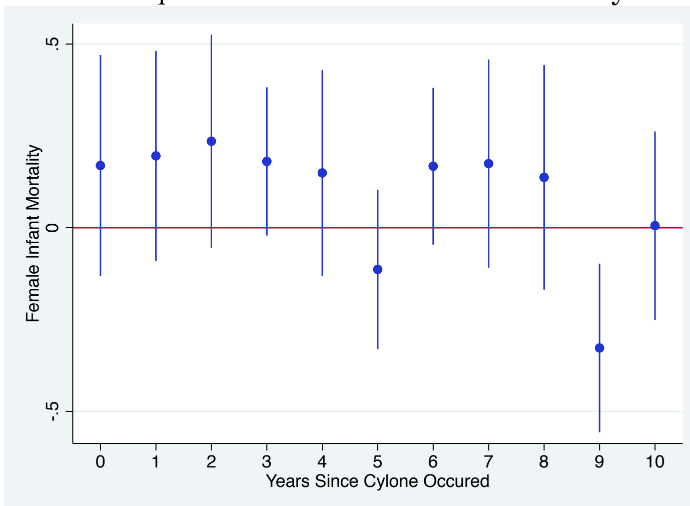

Figure 3: Coefficient Plot of Tropical Cyclone Exposure and Male Infant Mortality

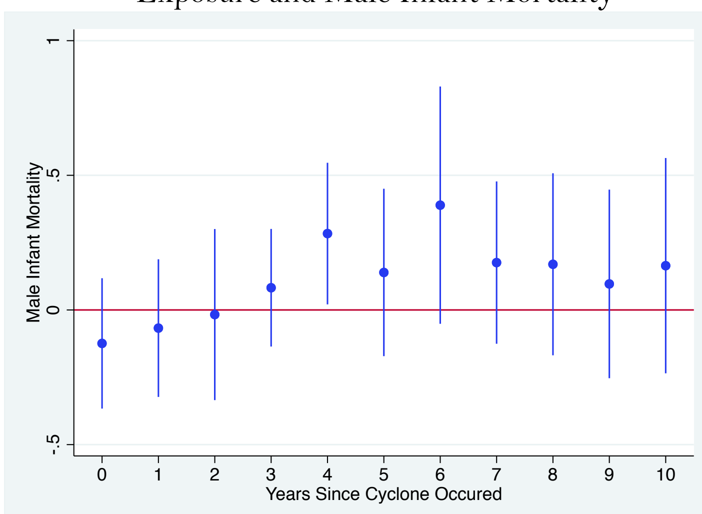

Figure 4: Coefficient Plot of Tropical Cyclone Exposure and Infant Mortality

Table 15: Global Impact of Average 8-year Lagged Exposure

	1	2	3
VARIABLES	Female	Male	Both
Max wind speed	0.222	-0.122	0.0455
	(0.158)	(0.129)	(0.103)
AvgExposure	1.303*	1.008	1.141*
	(0.663)	(0.687)	(0.598)
Constant	38.14***	52.16***	45.35***
	(5.730)	(5.338)	(4.912)
Observations	256,530	268,052	524,592
R-squared	0.039	0.041	0.039

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 5: Coefficients of Global Impact of Average 8-year Lagged Exposure

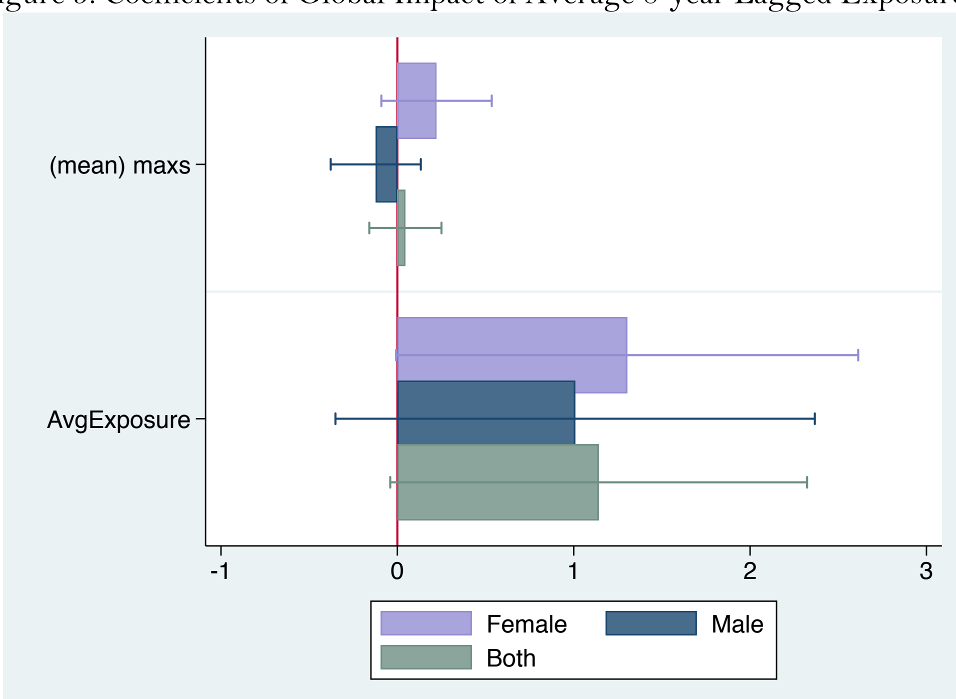

Table 16: Robustness Check Lead and Lagged Exposure

VARIABLES	(1) Female	(2) Male	(3) Both
F1_max wind speed	0.0871	0.0349	0.0574
	(0.108)	(0.115)	(0.0909)
F2_max wind speed	0.125	0.135	0.134
	(0.118)	(0.157)	(0.109)
Max wind speed	0.184	-0.131	0.0243
	(0.162)	(0.124)	(0.110)
L1_max wind speed	0.201	-0.0563	0.0745
	(0.143)	(0.132)	(0.116)
L2_max wind speed	0.307**	0.0358	0.175
	(0.135)	(0.158)	(0.127)
L3_max wind speed	0.222**	0.0989	0.168**
	(0.0991)	(0.120)	(0.0837)
L4_max wind speed	0.205	0.286**	0.247**
	(0.151)	(0.131)	(0.116)
L5_max wind speed	-0.0812	0.121	0.0230
	(0.115)	(0.154)	(0.108)
L6_max wind speed	0.209*	0.396*	0.295**
	(0.113)	(0.222)	(0.134)
L7_max wind speed	0.176	0.151	0.144
	(0.144)	(0.151)	(0.110)
L8_max wind speed	0.175	0.170	0.163
	(0.152)	(0.170)	(0.116)
Constant	36.20***	49.64***	43.13***
	(6.262)	(6.410)	(5.613)
Observations	254,397	265,765	520,172
R-squared	0.039	0.041	0.039

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 6: Lead and Lag Coefficient Plot of Tropical Cyclone Exposure and Female Infant Mortality

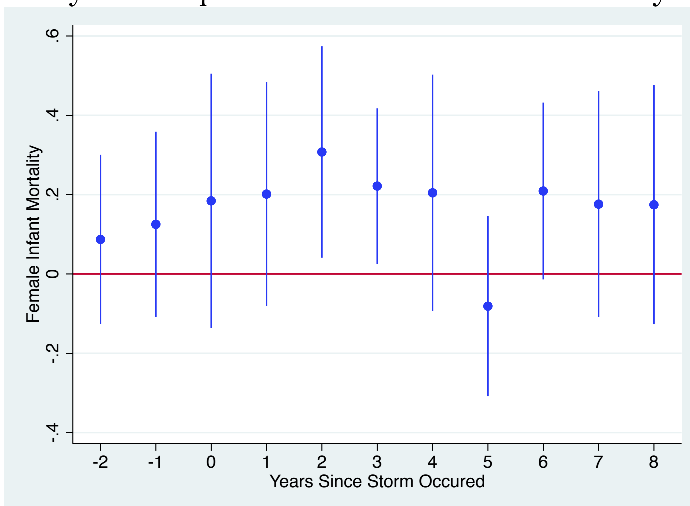

Figure 7: Lead and Lag Coefficient Plot of Tropical Cyclone Exposure and Male Infant Mortality

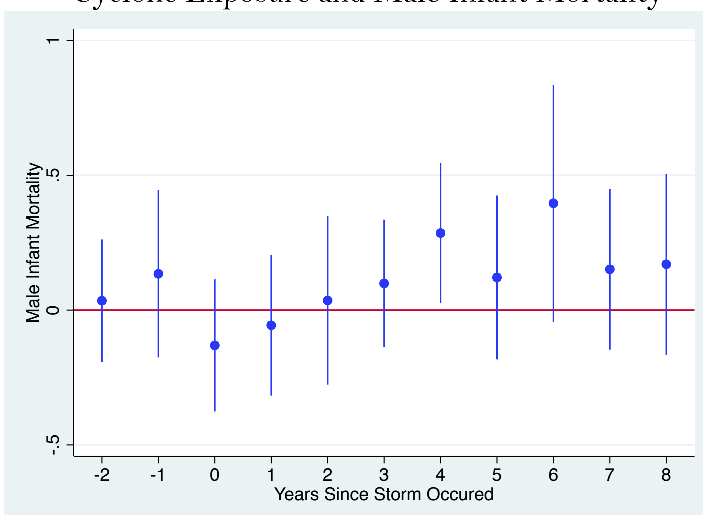

Figure 8: Lead and Lag Coefficient Plot of Tropical Cyclone Exposure and Infant Mortality

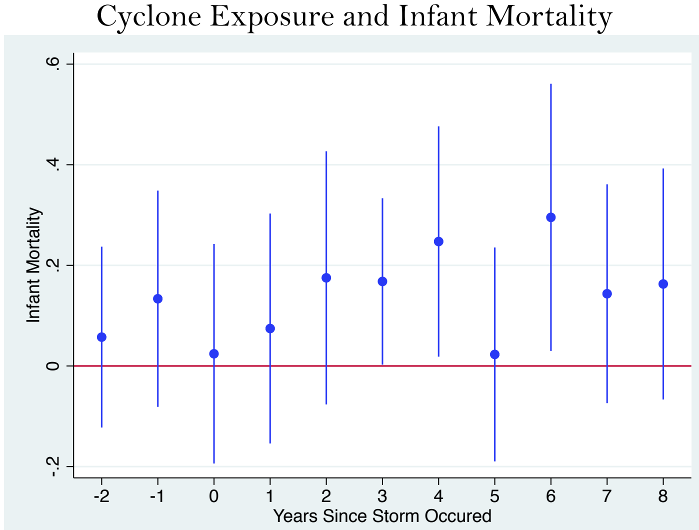

Table 17: Impact of Tropical Cyclone Exposure in Latin America

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	0.116	-0.0440	0.0256
	(0.170)	(0.189)	(0.135)
L1_max wind speed	0.0626	-0.165	-0.0533
	(0.248)	(0.213)	(0.210)
L2_max wind speed	0.253	0.117	0.189
	(0.194)	(0.162)	(0.132)
L3_max wind speed	0.598***	0.240	0.418***
	(0.181)	(0.166)	(0.119)
L4_max wind speed	0.536*	0.0703	0.292
	(0.294)	(0.266)	(0.212)
L5_max wind speed	-0.0862	-0.0764	-0.0671
	(0.161)	(0.238)	(0.138)
L6_max wind speed	0.219	0.555**	0.399**
	(0.255)	(0.233)	(0.179)
L7_max wind speed	0.110	-0.0687	0.0140
	(0.202)	(0.191)	(0.135)
L8_max wind speed	-0.0952	0.239	0.0794
	(0.174)	(0.258)	(0.130)
L9_max wind speed	-0.195	-0.279	-0.241*
	(0.196)	(0.188)	(0.133)
L10_max wind speed	0.00837	-0.0418	-0.0109
	(0.219)	(0.391)	(0.246)
Constant	28.48***	42.02***	35.30***
	(6.965)	(7.243)	(4.995)
Observations	83,719	86,973	170,693
R-squared	0.022	0.027	0.024

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Impact of Tropical Cyclone Exposure in Asia

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	-0.147	-0.0440	0.0256
	(0.154)	(0.189)	(0.135)
L1_max wind speed	0.287	-0.165	-0.0533
	(0.175)	(0.213)	(0.210)
L2_max wind speed	0.0484	0.117	0.189
	(0.147)	(0.162)	(0.132)
L3_max wind speed	0.129	0.240	0.418***
	(0.151)	(0.166)	(0.119)
L4_max wind speed	-0.146	0.0703	0.292
	(0.131)	(0.266)	(0.212)
L5_max wind speed	-0.242	-0.0764	-0.0671
	(0.201)	(0.238)	(0.138)
L6_max wind speed	0.175	0.555**	0.399**
	(0.155)	(0.233)	(0.179)
L7_max wind speed	-0.145	-0.0687	0.0140
	(0.184)	(0.191)	(0.135)
L8_max wind speed	-0.00960	0.239	0.0794
	(0.180)	(0.258)	(0.130)
L9_max wind speed	-0.288*	-0.279	-0.241*
	(0.151)	(0.188)	(0.133)
L10_max wind speed	-0.0496	-0.0418	-0.0109
	(0.141)	(0.391)	(0.246)
Constant	46.55***	42.02***	35.30***
	(8.288)	(7.243)	(4.995)
Observations	125,429	86,973	170,693
R-squared	0.039	0.027	0.024

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Impact of Tropical Cyclone Exposure in South-East Asia

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	-0.150	-0.211	-0.177
	(0.182)	(0.176)	(0.121)
L1_max wind speed	0.450**	0.0823	0.266**
	(0.210)	(0.194)	(0.115)
L2_max wind speed	-0.0171	-0.145	-0.0858
	(0.172)	(0.257)	(0.155)
L3_max wind speed	0.203	-0.298*	-0.0485
	(0.175)	(0.163)	(0.128)
L4_max wind speed	-0.124	0.0819	-0.0143
	(0.160)	(0.156)	(0.118)
L5_max wind speed	-0.247	-0.229	-0.222
	(0.246)	(0.203)	(0.165)
L6_max wind speed	0.229	0.0278	0.129
	(0.191)	(0.225)	(0.128)
L7_max wind speed	-0.141	0.222	0.0435
	(0.218)	(0.216)	(0.143)
L8_max wind speed	0.0848	0.429	0.268*
	(0.216)	(0.282)	(0.138)
L9_max wind speed	-0.305*	0.381*	0.0380
	(0.172)	(0.196)	(0.111)
L10_max wind speed	0.00596	0.291	0.145
	(0.156)	(0.257)	(0.154)
Constant	41.56***	44.93***	43.04***
	(11.72)	(12.56)	(7.399)
Observations	52,290	55,224	107,517
R-squared	0.041	0.041	0.039

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20: Impact of Tropical Cyclone Exposure in Africa

VARIABLES	(1) Female	(2) Male	(3) Both
Max wind speed	0.494	-0.0436	0.220
	(0.340)	(0.269)	(0.264)
L1_max wind speed	0.168	0.0441	0.110
	(0.281)	(0.251)	(0.225)
L2_max wind speed	0.581	-0.128	0.219
	(0.405)	(0.355)	(0.342)
L3_max wind speed	-0.194	0.224	0.0292
	(0.183)	(0.201)	(0.132)
L4_max wind speed	0.122	0.567**	0.353
	(0.260)	(0.251)	(0.220)
L5_max wind speed	0.123	0.529*	0.314
	(0.211)	(0.302)	(0.209)
L6_max wind speed	0.0757	0.485	0.248
	(0.176)	(0.552)	(0.315)
L7_max wind speed	0.491*	0.525*	0.459**
	(0.269)	(0.268)	(0.194)
L8_max wind speed	0.607	-0.240	0.136
	(0.388)	(0.331)	(0.304)
L9_max wind speed	-0.566*	0.447	-0.0608
	(0.277)	(0.533)	(0.208)
L10_max wind speed	0.196	0.365	0.280
	(0.314)	(0.400)	(0.252)
Constant	54.36***	61.89***	58.89***
	(11.02)	(13.19)	(10.97)
Observations	47,346	48,506	95,852
R-squared	0.043	0.043	0.041

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1