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Abstract

This study analyzes the effects of exposure to tropical storms and hurricanes during pregnancy on children's anthropometric measurements taken within the first five years of life. It combines destruction indexes at the district level with 13 yearly rounds of household level surveys from Jamaica. The empirical strategy exploits variation arising from the storms' timing and intensity across different cohorts within the same district. The findings suggest that when expectant mothers living in coastal-rural areas are affected by at least two hurricanes, their children are 56 percentage points more likely to show low birth weight. Furthermore, these children also experience negative impacts on anthropometric measurements taken within the first five years of life equivalent to 1.88 standard deviations in weight-for-age and 1.4 standard deviations in weight-for-height.

JEL classification: I12, J13, O15, Q54
Keywords: Jamaica, anthropometric measurements, tropical storms

1. Introduction

This study analyses the effects of weather shocks suffered during pregnancy on humans' early physical development. The study provides evidence related to the “fetal origins” hypothesis pioneered by Barker (1990) focusing on the effects of tropical storms and hurricanes that occur during gestation periods on anthropometric measurements taken during the first five years of life.[1] We exploit anthropometric measurements taken from children born between 1988 and 2012 in Jamaica along with geocoded information of tropical storms occurred during their pregnancy periods.

This paper is related to the literature on the socioeconomic effects of natural disasters like hurricanes and earthquakes studied by Baez and Santos, 2007, who using household data from Nicaragua and a difference in differences method exploiting exogenous variation of Hurricane Mitch’s trajectory, find that hurricanes reduce access to health care in the medium term. Caruso and Miller, 2015, using data from Peru’s census, exploited variation from an earthquake and found that adults who were affected when they were in utero attain less years of schooling than those who were not affected. Currie and Rossin-Slater, 2013, using birth certificate data from Texas, exploited exogenous variation from the trajectory of hurricanes and found a negative effect of these events on new born outcomes such as delivery complications and time in an incubator after birth. Frankenberg, et. al, 2013 used a very detailed survey data on children conducted before and after the tsunami in Indonesia to study the response of children’s height to the shock and found a heterogeneous effect at the time of the event. Hoddinott and Kinsey, 2001 using household panel data from Zimbabwe and exploiting variation from a larger-than-average drought the found that children exposed to the event have negative growth outcomes on height. Imberman, Kugler, and Sacerdote, 2012, using data at the individual level from education institutions, exploited variation from hurricanes Sandy and Katrina and found a negative effect on school performance in the aftermath of the event. Sotomayor, 2013, using data from health conditions and exploiting variation from hurricanes and tropical storms between 1920 and 1940, found negative effects on health conditions such as high blood pressure associated with exposure to the events when they were in utero. Our study is also related to several papers that explore the effects on children’s outcomes as a result of different situations experienced while they were in utero. See Case, Lubotsky, and Paxson (2002), Gutierrez (2013), and Kiernan and Huerta (2008) for events related to

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[1] The hypothesis argues that the intra-uterine environment (especially nutrition) “programs” the fetus to have specific metabolic characteristics, which can lead to future disease.

economic hardship. Using panel data, they found that adult's heath was negatively affected by differences in levels of income and wealth and economic crisis when exposed to these shocks during infancy; Lewis et al. (2014) study the effects of exposure to alcohol in-utero using panel data from the UK; and Schultz-Nielsen et al. (2014) study how nutritional deficiency during gestation due to the Ramadan caused negative effects on adult's labor outcomes. More generally, our study is related to the set of studies exploring the medium- and long-term consequences of shocks suffered during early stages of development. Almond and Currie (2011) and Almond, Currie, and Duque (2017) provide comprehensive reviews of these studies. The common factor in the literature is that stressful events suffered during early stages of development generate negative impacts over the short, medium, and long term.

A strand of this literature focuses on the stress suffered by expectant mothers and its effect on in-utero development. Agüero (2014) and Hu and Li (2016) investigate the effects of high temperatures on birth weight and adult height using data from cross section household data from Mexico and China, respectively; Almond and Mazumder (2011) study the effects of nutritional deprivation during Ramadan on birth weight using microdata from Michigan in the USA and census data from Uganda and Iraq. Camacho (2008) studies the effects of acts of terrorism (as a source of maternal stress during pregnancy) on birth weight; and Lavy, Schlosser, and Shany (2016) focus on stressful migration episodes. Overall, these studies find negative effects that could last throughout the children's lives. Glynn et al. (2001) conducted a study on how natural disasters like earthquakes create negative conditions for a normal fetus' development using data from California. The authors claim that stress suffered due to the impact of this kind of event has a worse effect at the beginning of gestation; this negative effect will decrease as gestation advances, since psychologically, mothers become increasingly resilient to hardships.

We contribute to the international literature investigating the effects of tropical storms and hurricanes suffered during pregnancy on early childhood physical development. Our strategy allows an exploration of the possibility of nonlinear effects with respect to the intensity of the destruction suffered during pregnancy. To do so, we use all storms that affected the North Atlantic region between 1987 and 2012. These include hurricanes between categories 1 and 2 and tropical storms (which are weaker than hurricanes but are accompanied by more precipitation). To our knowledge, this is the first study exploring these issues in a country in the Caribbean, a region that is exposed to recurrent weather shocks.

Our findings suggest that expectant mothers living in coastal-rural areas exposed to an average of at least two hurricanes during their second trimester of gestation are 56 percentage points more likely to deliver a baby with low birth weight (i.e., below 2.5 kg). In addition, this exposure during the third trimester of gestation causes a reduction in children's weight-for-age (weight-for-height) measured within the first five years of life, equivalent to 1.88 (1.4) standard deviations. Considering the well-documented deleterious effects of low birth weight on educational and labour market outcomes (Black, Devereux, and Salvanes, 2007; Currie and Moretti, 2007; Oreopoulos et. al, 2008; and Royer, 2009) our findings highlight the importance of having appropriate safety nets in place to assist expectant mothers who experience such events. Taking the findings in Black, Devereux, and Salvanes (2007) as a benchmark, our estimates imply that Jamaican children exposed to two or more hurricanes during their mother's pregnancy will be 2.76 percent less likely to graduate from high school, will have 2.76 percent lower IQ (for boys), and will have 2.07 percent lower earnings in adulthood compared to similar children who did not experience these shocks while in utero.

The remainder of the document is organised as follows. Section 2 provides a brief background on the Jamaican economy. Section 3 describes the data, while Section 4 shows the construction of the destruction measures based on the storms' physical characteristics. The empirical strategy is developed in Section 5. Results are discussed in Section 6, Section 7 analyses the robustness of our results, and Section 8 concludes.

2. Country Background

With a population of 2.7 million and a per capita GDP of US$8,872, Jamaica is a middle-income, small island economy.[2] Located in the Caribbean hurricane belt, Jamaica has averaged two storm events per year between 1990 and 2012. The frequency of storm events has been higher in more recent years, as there were 29 events in the 2000s compared to 11 in the 1990s.

Jamaica is the third largest island in the Caribbean after Cuba and Hispaniola. The country has a varied topography, comprising the eastern mountains with a maximum elevation of 7,402 feet, the central valleys and plateaus, and the coastal plains, where

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[2] Population data are from the 2011 Jamaica census; GDP is 2015 per capita purchasing power parity (PPP) from the World Development Indicators.

most of the population resides. The urban population comprised 53.9 percent of the total in 2011, compared to 49.7 percent in 1991 and 52.1 percent in 2001.

Historically, Jamaica’s economic growth has been slower than that of other countries in the region. Average annual economic growth over the observation period 1993–2012 in Jamaica was 0.54 percent, compared to 3.2 percent for the Latin America and the Caribbean region. The period includes three periods of economic contraction, 1996–98, 2008–10, and 2012.

Unemployment over the whole period averaged 13.5 percent, peaking at 16.5 percent in 1997 and falling below 10 percent only in 2006 and 2007 (9.6 and 9.4 percent, respectively). The headcount ratio of poverty declined from a peak of over 40 percent in 1991 to 9.9 percent in 2007. The recession accompanying the world economic downturn led to a renewed increase in poverty to 19.9 percent in 2012, which fell slightly to 18.7 percent in 2016.

Jamaica’s economy is highly dependent on services, particularly tourism, for which the country is famous. The contribution of agriculture to total GDP has been low for an extended period, at 8.3 percent in the 1990s, further declining to 6.8 percent by 2012. Over the same period, industry’s contribution to GDP declined from 37 to 21 percent of total GDP, while services increased from 55 to over 70 percent.

Agriculture remains an important sector, however, as it employs a disproportionate share of the labour force, especially in rural areas. In 2012, agriculture employed on average 16.7 percent of the classifiable workforce, second only to wholesale and retail repair of motor vehicle and equipment, which averaged 20 percent.

3. The Data

The data for our study are derived from two sources. First, we use yearly rounds of Jamaica's Survey of Living Conditions (SLC) from 1993 to 2012.[3] The SLC is a nationally representative survey executed every year on a sub-sample of households interviewed in the second quarter of the Labour Force Survey (the “April LFS”). The SLC contains information on individuals’ sociodemographic characteristics, district of residence, and a detailed module for children under 5 which collects birth weight, anthropometric

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[3] We did not use the 1994, 1995, 2003, 2005, and 2009 rounds as they did not include the anthropometric module. Since 2001 and 2011 were census years, the SLC was not executed.

measurements, and vaccination status.[4] Appendix 1 contains detailed descriptions of the LFS and the SLC designs.

Using the SLC collected data on height, weight, age, and the World Health Organization (WHO) z-scores tables, we calculated standardised measures of weight-for-height, weight-for-age, and height-for-age. The total sample size is roughly 14,000 children under 60 months of age after selecting only individuals with standardised scores between -5 and 5. Of these, 2,569 reside in the coastal-rural region.

Tropical storms particularly affect households located in the coastal-rural region in two ways. First, poverty rates are higher in rural areas, and second, proximity to the coast makes them particularly vulnerable to storms coming from the ocean. Their lack of consumption-smoothing mechanisms (precautionary savings and/or access to sources of finance), coupled with their dependence on natural resources, generate an increasing exposure to risk and an inability to cope with it, as Hallagate et al. (2015) suggest.

Table 1 presents descriptive statistics for both the complete and the coastal-rural samples. The coastal-rural area differs from the complete sample in some respects. Children from the coastal-rural area live in households with fewer members and with heads who are less likely to have tertiary education. In terms of outcomes, while the average birth weight of children living in the coastal-rural area is similar to that of the full sample, the incidence of low birth weight is higher in coastal-rural areas. Children in Jamaica show average anthropometric z-scores of approximately 0.20 standard deviations higher that the international WHO benchmarks. However, the complete sample has higher weight-for-height (ZWH) and lower height-for-age (ZWA) than children living in coastal-rural areas. Vaccination rates of children residing in coastal-rural areas and the full sample are equivalent.

Our second data source is the International Best Track Archive for Climate Stewardship (IBTrACS), managed by the National Oceanic and Atmospheric Administration (NOAA). This dataset contains information on every storm occurred between 1969 and 2014, including date, trajectory, maximum sustained wind, radius of maximum speed, and minimum central pressure. This information is collected every six hours during the storm's lifespan and will be used to build the wind field model that is the basis for the calculation of destruction measures. Appendix Table 1 shows the dates of the storms included in our analyses, the maximum wind speed, and the category of the

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[4] The April LFS execution period is between April and June. The SLC execution period regularly goes from June to November visiting a nationally representative subsample of the April LFS.

storm (Saffir-Simpson Scale). Appendix Figure 1.a shows the distribution over the space of the storms studied and Appendix Figure 1.b shows a satellite photograph of hurricane Ivan in 2004 while approaching to the island.[5] The sample is comprised of storms that are at maximum 500 Km from the island's coast since the potential diameter of the storm can reach 1000 Km, as in the photograph.

4. Wind Field Model and Storm Destruction Measure

Following Strobl (2012), who based his analysis on Boose, Serrano, and Foster (2004), we calculated an approximation of the storms' local wind speed in every district in Jamaica. The wind field model is based on the model suggested by Holland (1980) for cyclostrophic wind and sustained wind speed as follows:

$$V_{s,d,r} = G \cdot F \left[V_m - S(1 - \sin(T_d))\frac{V_h}{2}\right]\left[\left(\frac{R_m}{R_d}\right)^B exp\left(1 - \left[\frac{R_m}{R_d}\right]^B\right)\right]^{1/2} \tag{1}$$

where $V_{s,d,r}$ is the estimate of storm *s* wind speed, in district *d,* within a time interval *r*. *G* is the gust factor, F is the surface friction, V_m is the maximum sustained wind velocity that the storm reaches at any point, *S* is the asymmetry due to forward motion of the storm, T_d is the clockwise angle between the storm's forward path and the ray between the storm's center and the district's centroid *d*, V_h is the forward storm's speed, R_m is the radius of maximum winds, R_d is the length of the ray that connects the storm's center and the district's centroid *d*, and *B* is the shape of the wind profile curve-scaling parameter.[6]

From this point on, we diverge from the Strobl (2012) destruction measure. The author proposes an index that uses a set of weights to consider local characteristics such as population growth. Unlike Strobl (2012), we are not interested in approximating a destruction measure at the national level, since we are exploiting variation at the district level. Therefore, we calculate the destruction measure at the district level as follows:

$$WIND_{s,d} = \int_t^\tau V_{s,d,r}^{3.8} dr \tag{2}$$

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[5] https://visibleearth.nasa.gov/view.php?id=71977

[6] *F*, *S*, and *B* parameters were taken from Strobl (2012) and Boose, Serrano, and Foster (2004).

where $WIND_{s,d}$ is the destruction measure estimated for storm s within district d that is equal to the summation of the values of wind field to some power. Then, for each six-hour observation, we estimate the wind field model $V_{s,d,r}$ restricted to districts that are between 0 and 500 km away from the storm.[7] The 3.8th power used for the wind model follows the relation found by Strobl (2012) between total costs due to hurricanes and the maximum observed wind speeds of the hurricane.[8] To match the total $WIND_{s,d}$ that pregnant women received in each quarter of gestation, we use information on birth and storm dates. The SLC contains information on the date of birth, and the NOAA IBTrACS storm data contains the date of the event. Therefore, we determine the total exposure of the child at each moment between the first and the third trimester of gestation.[9] The strategy to match children and storms is as follows:

Step 1. Denoting child *i* date of birth as D_i^b and D_s as the day of storm *s*, we determine if the individual was hit in a determined period as follows:

1. If $D_s - D_i^b \in [-270; -181]$ days, individual was hit in the first trimester of gestation;
2. If $D_s - D_i^b \in [-180; -91]$ days, individual was hit in the second trimester of gestation;
3. If $D_s - D_i^b \in [-90; 0]$ days, individual was hit in the third trimester of gestation;

Therefore, we define a group of indicator variables denoting if each child *i* was affected by any storm during each gestation period.

Step 2. The indicators created above have a value one if a storm *s* hit child *i* in period of gestation *p;* while zero otherwise. We then calculate the destructive power received by child *i* during gestation period *p* coming from storm *s,* by multiplying the correspondent destruction variable for storm *s* ($WIND_{s,d}$) times the indicator correspondent to child *i*, living in district *d*, during gestation period *p*. Finally, we add the destructive power of all the storms over period *p* which hit each child *i*. For example, if a child was hit by four different storms in her first trimester in the womb, the value of the destructive power received for that trimester is the total wind received resulting from adding the four individual destruction measures.

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[7] As mentioned in Strobl (2012), this assumption relies on the fact that major storms can reach a diameter of 1000 km.

[8] To extended explanation about the power parameter used, see Strobl (2012).

[9] We do not have information about the exact amount of time that the individual was in utero, so we assume that all of them were born full term (i.e., at 270 days of gestation).

5. Empirical Strategy

Our main question is whether environmental conditions suffered during gestation periods affect children's physical development within their first five years of life. To disentangle causality between environmental shocks and health outcomes, we use a destruction variable created from the storms' physical characteristics (wind speed, distance to district, trajectory, etc.), that are random and exogenous events in intensity, trajectory, and life span. We define the outcome variables as standardised versions (using WHO tables) of anthropometric measurements such as weight-for-height, weight-for-age, and height-for-age as well as birth weight (in kg) and the likelihood of being born with low birth weight (below 2.5 kg).

Following Dell, Olken, and Jones (2014), the main econometric model is as follows:

$$Z_{i,d,c} = \delta_d + \delta_c + \delta_s + \delta_d \cdot TREND + \sum_{p=1}^{3} \sum_{y=1}^{3} \left[\beta_{y,p} \cdot Q_{i,d,c,p}^{y} \right] + X'\gamma + \varepsilon_{i,d,c} \qquad (3)$$

where $Z_{i,d,c}$ is the outcome for child *i* born in district *d* who belongs to cohort *c* (month-year of birth). δ_d and δ_c are fixed effects at the district and cohort level, $\delta_d \cdot TREND$ is a district linear trend on children's birth year that absorbs long-term linear trends in the outcome that can vary depending on the district. δ_s is a fixed effect of the survey year. $Q_{i,d,c,p}^{y}$ is the total amount of destructive power (*WIND)* that child *i,* born in district *d,* who belongs to cohort *c* received during gestation trimester *p* elevated to the power *y*. Lastly, X is a vector of household and individual sociodemographic characteristics including household head's education, age, and gender, household size, number of individuals in household aged 0–5, 6–14, 15–24, and 25–49, and child's age and gender. Under this framework, estimates of $\beta_{1,p}$, $\beta_{2,p}$ and $\beta_{3,p}$ for $p \in \{1,2,3\}$ capture the relationship between destructive power received during gestation trimester p and the outcome of interest.

Model (3) controls for all time-invariant unobserved characteristics at the district level through the district fixed effects. The cohort fixed effects control for seasonal patterns, ameliorating potential selection bias that mothers could have with respect to the timing of pregnancy decisions. The year of survey fixed effects controls for non-observable characteristics that might have affected children's measurement processes within each survey round. Lastly, time-variant characteristics at the district level are controlled through the inclusion of differential linear time trends by district.

Following the literature and the continuous nature of treatment, we allow a nonlinear relationship between the destruction measure and the outcomes of interest. Maccini and Yang (2009) found a positive relationship between rainfall and some welfare-related outcomes when evaluating the effect of that shock on the first year of life. When the shock is large, like the terrorist attacks studied by Camacho (2008), the effect is negative. However, when the event is of much higher magnitude, like the tsunami in Indonesia studied by Frankenberg, Friedman, and Ingwersen (2013), the effect of the aid received in the aftermath of the event could push the outcome variable up, given that aid may offset the negative impact of the event. Therefore, to capture the potential nonlinearity of effects, we consider a third-degree polynomial of the destruction measure.

An important aspect of this model is the necessity of treatment variation within the same cohorts. Following Cummins (2015), there is a potential bias that affects estimation when cross-sectional data are used to estimate effects of certain treatments that are applied at the cohort level. The problem relies on the potential unobserved relation between treatment exposure and age-at-measurement within the same cohort. The author claims that this bias can potentially be avoided if there is variation in treatment intensity within the same cohort so that it is possible to disentangle the cohort effect from the treatment effect. As mentioned before, variation of district-level destruction measures within the same cohorts allows us to distinguish storm effects form cohort effects.

Potential sources of bias could arise from selection and migration. It is possible that parents self-select to give birth in the first six months of the year, when there are usually no storms. The second source of selection bias is the potential effect of storms on survival rates such that the resulting observed sample comprises individuals with different potential outcomes than those who were not observed because they died before the survey date. The third source of selection bias is potential migration due to storms. The final source is the assumption that the district of birth was equivalent to the district where the mothers lived during pregnancy. If the mother's location during pregnancy was different from the place of birth used to impute the district-level destruction measures, then our results could be biased. We show that our strategy and results are robust to all these potential identification threats in Section 7.

6. Results

Our results not only report point estimates, but also primarily explore the existence of heterogeneous effects with respect to the intensity of exposure. To do so, we evaluate the cubic polynomial of the estimated impact parameters from model (3) at different values of the destruction measure received within each trimester of gestation. As such, potential nonlinear relationships between total exposure to storms and outcomes of interest are presented.

The most common weather events in the Caribbean are tropical depressions and storms. Within our study period, 75 percent of the events were either depressions or storms. These events are less destructive than hurricanes in terms of wind power and gust factor. Tropical storms and depressions are characterised by an increase in rainfall but generally do not cause serious damage to crop production or road infrastructure.

Our study period also contains some of the most destructive events ever registered in the Caribbean Basin. Twenty-five percent of the events are category 1 and 2 hurricanes on the Saffir-Simpson scale. Some of the most renowned hurricanes are Gilbert in 1988, Gustav in 2008, Ivan in 2004, and Mitch in 1998. These events had devastating impacts on infrastructure. These include destruction of road infrastructure, which severely hampered rapid emergency response; increased housing shortages due to reduction of inhabitable units; reduced access to energy and water; and increased food insecurity due to crop destruction.

6.1. Effects of Tropical Storms

We start assessing the estimated impacts of the average tropical storm (excluding hurricanes) that occurred within each trimester of gestation. Table 2 shows the estimated impacts for the full national sample suggesting the absence of effects. However, when focusing on the coastal-rural population in Table 3, we observe some mild positive effects of storms occurring during the second trimester of pregnancy equivalent to 0.04 kg in birth weight but no effects on the likelihood of low birth weight. In addition, we also observe positive effects on both ZWH and ZWA standardised scores measured within the first 60 months of life. These are equivalent to 0.08 (0.07) and 0.06 (0.06) standard deviations in ZWH (ZWA) following storms experienced within the second and third trimesters of pregnancy, respectively.

Therefore, we observe some positive effects when children are hit by tropical storms in their second and third trimesters of gestation. This suggests that, when exposed to events low in power (like tropical depressions), some benefits could come with the extra rainfall fostering agricultural output. This could be translated into improved nutrition during pregnancy (either through an income or own production effect). However, the lack of data prevents us from testing and disentangling these possible transmission channels directly.[10] The next section will show some indirect evidence on this probable transmission channel.

6.2. Effects of an Average Hurricane

In this section, we document the estimated effects of an average storm that included one hurricane. Table 4 shows the estimated effects for the full national sample suggesting no discernible impacts. However, when focusing on the coastal-rural sample in Table 5, estimates suggest some positive effects of being exposed to an average hurricane during the second trimester of gestation. These effects are equivalent to 0.35 kg in birth weight, 0.91 standard deviations in ZWH, and 0.79 standard deviations in ZWA.

While these results may appear to be counterintuitive, the accumulated destructive power of an average storm including one hurricane falls below the mean of the destructive power distribution of all storms observed in the study period. Figures 1 to 3 show the estimated effects of the storms' destructive power experienced during each trimester of gestation on the outcomes of interest. The point estimates shown in Table 5 correspond to the second vertical line in the figures. Therefore, the destructive power of an average hurricane is not yet an extremely destructive event. As such, the few positive effects observed could be in line with the positive effects associated with increased rainfall and agricultural output.

6.3. Effects of Destructive Hurricanes

The study also focused on the effects of storms that included two or more hurricanes. Table 6 shows full-sample estimated effects associated with destruction measures equivalent to an average storm that included at least two hurricanes. While impacts on birth weight are negative in sign, they are imprecisely estimated. However, we observe significant impacts, suggesting an increased likelihood of the occurrence of low birth weight. It appears that pregnant women exposed to these events during their second (third) trimester increase the likelihood of delivering a baby with low birth weight by 20 (17)

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[10] Data on own production and income is present in the data, however the survey's framing structure does not allow us to detect how storms affect these variables. In the case of self-production and consumption of food, the recall period is four weeks, and this coupled with the fact that the survey is implemented between May and August (before storm season) makes impossible to identify storm's effect.

percentage points. These estimated effects are twice as large as the overall mean of an 8 percent incidence of low birth weight (reported in Table 1).

When focusing on the coastal-rural sample (Table 7), estimated effects are larger. The estimated impacts on birth weight are negative, around 0.7 kg for the first and second trimesters (although imprecisely estimated for the second trimester). These findings are consistent with Camacho (2008), where birth weight effects rose when exposed to shocks during the first and second trimesters of gestation. However, our results are larger. While Camacho (2008) estimated a reduction in birth weight of 11.6 grams when exposed to land mines in the second trimester of gestation, our estimate finds a reduction of 730 grams.[11] In addition, we find that the likelihood of delivering a low-birth-weight baby increases by 56 percentage points if the storm is experienced during the second trimester of gestation (effect equivalent of 5 times the overall mean of 11 percent for the coastal-rural area).

The negative effects on birth weight are particularly relevant, as previous literature has documented a long-term negative impact of lower birth weight on educational and labour market outcomes (Black, Devereux, and Salvanes, 2007; Currie and Moretti, 2007; Oreopoulos et al., 2008; Royer, 2009). For example, taking the findings in Black, Devereux, and Salvanes (2007) as a benchmark, our estimates imply that Jamaican children exposed to two or more hurricanes during the mother's pregnancy will be 2.76 percent less likely to graduate from high school, will have 2.76 percent lower IQ (for boys), and will have 2.07 percent lower adult earnings when compared to similar children who did not experience these shocks while in utero. Therefore, our findings highlight the importance of having appropriate safety nets in place to assist expectant mothers experiencing such events.

Regarding ZWH, we find negative effects equivalent to 1.4 standard deviations due to experiencing the storm during the third trimester of gestation. Compared to Baez and Santos (2007), who studied the effects of hurricane Mitch in Nicaragua, our result is almost three times larger than their estimate of 0.493 of a standard deviation in ZWH.

In contrast with ZWH, ZWA is a longer-term outcome since it is more difficult to be improved with better subsequent nutrition than ZWH. We observe a negative effect equivalent to 1.88 standard deviations in ZWA due to experiencing the storm within the

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[11] The data from Camacho (2008) present an average birth weight of 3.153 kg while the mean for Jamaica is about 3.184 kg. However, the share of low birth weight—less than 2.5 kg—in Jamaica exceeds that of Colombia (11 percent in Jamaica's rural-coastal sample versus 7.74 percent in Colombia).

third trimester of gestation. Compared with that of Kumar, Molitor and Vollmer (2014), our estimate is 12 times larger with respect to the negative documented effect of droughts on ZWA in India.[12]

The previous estimates correspond to the third vertical line in Figures 1 to 3. As these figures show, the relationship between the destructive power of the storms and the outcomes of interest is nonlinear. In general, we observe that the effects begin from zero to slightly positive when storms are in the left tail of the destructive power. However, as the destructive power of storms increase, the effects on the outcomes of interest turn negative (with some flattening out and even turning to positive effects for extremely destructive events on the right tail of the distribution).

The nonlinearity of the effects and the flattening of the curves for extremely catastrophic events are consistent with Frankenberg, Friedman, and Ingwersen (2013). In this study, the authors find a positive effect of the tsunami on children's height, suggesting that this class of extreme events could come with "massive influx of humanitarian aid and the accompanying resources following the tsunami." (Frank, Friedman, and Ingwersen, 2013: page 12). This behaviour could push outcome variables up since food intake could increase and, in some cases, improve.

The effects that we document are likely lower bounds due to measurement error. Our destruction measure was built using data from the six-hour interval records from NOAA archives. This is the smallest time interval available and, therefore, the exact path followed by the storm at each stage of its life cannot be exactly recreated. In addition, the measure of total exposure by an individual is calculated using the geometric distance between the storm and the centroid of the district of residency, which is not the exact location of residency. Despite these limitations, our results are robust to several sources of possible biases, as we show in the next section.

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[12] The authors found that the larger effect of drought is about 0.15 of a standard deviation when children were exposed to droughts during the gestation period.

7. Robustness Analysis and Theory of Change.

We think that our results are driven by the variation in access to proper nutrients intake. We test this hypothesis using data from districts' geographic size and the road network of Jamaica. With these variables, we divide the sample by size of the district (small, medium, and large) and also by the level of road density (a measure that takes into account the number of roads within the district). We found that the effects are stronger when tested in sample living in small districts and where the road density is high. We also find that the estimated impacts are weaker in districts of large size and low connectivity.[13] This finding allows us to think—although the exploration of new data is needed—that people living in small and well-connected districts are prone to produce tradable crops, making their consumption dependent on their capacity for income generation, which is potentially affected by the storms. On the other hand, people living in larger districts that are less connected tend to produce crops for their own consumption instead of tradable ones, making their consumption dependent on crops that could be less affected by the storms such as root crops, compared to the other group.[14]

Partial empirical support to the previous hypothesis can be provided by observing the relationship between our destruction measure and agricultural output. Figure 4 uses quarterly output data from the Ministry of Agriculture to plot the relationship between output (*log*(tons)) and the destruction measure (*log*(Wind)).[15] The figure suggests that output behaves as a concave function of the destruction measure. Depending on the crop, output behaves as either an increasing or flat function of the destruction index up to a certain threshold. Once the threshold is reached (approximately between the equivalent of one average hurricane and the combination of hurricanes and other sub-categories of storms) output starts a decreasing pattern. Once this threshold is reached, an increase of 8 log-points in the storm's destructive power is associated with a decrease of approximately 48,550 tons of total agricultural output. Although analysis of georeferenced data on crops is needed, this cannot be done at this time due to lack of information of this kind.

Our strategy faces several potential sources of bias. This section shows that our results are robust to them. First, parents could self-select the time of conception and, therefore,

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[13] We observe in the data that the smaller districts are the ones with larger connectivity.

[14] The figures for this analysis will be available upon request to the authors.

[15] Ministry of Industry, Commerce, Agriculture and Fisheries: All Island Estimates of Production for Domestic Crops http://www.moa.gov.jm/AgriData/index.php

the birth period. Parents could decide to have their children in the first half of the year (i.e., in the non-storm season). If this were the case, we should observe a conglomeration of live births during the non-storm season. Figure 5 shows the frequencies of births by day of the year, pooling years of birth from 1988 to 2012. The figure shows that there is no season in which a discernible mass of live births is concentrated.

Second, if our strategy resembles a good source of exogenous variation, we should not observe a systematic relation between our destruction measure and characteristics that could be related with the outcomes of interest. To test for this, we run model (3) using the sociodemographic characteristics of household heads as outcomes. As can be seen in Appendix Table 2, out of 117 estimated parameters, only seven (or 6 percent) were statistically significant at the 10 percent level or lower. This provides further confidence on the conditional exogeneity of the destruction measure within our empirical strategy.

Third, although women may not choose to give birth purposely in the non-storm season, they could adapt to climatic conditions. Adaptation to storms could potentially ameliorate the estimated effects. Therefore, to test if women are adapting, we created an indicator for wall quality that equals *one* if wall material is brick, concrete nog, or concrete, while zero otherwise. We then aggregated the destruction that the district where the household resides suffered in the 12 months preceding the survey date. We then estimated model (3) using this indicator as an outcome. Appendix Table 3 shows that exposure to storms within the previous 12 months do not affect the wall materials. Therefore, we interpret this as weak evidence of infrastructure adaptation mechanisms.

Fourth, as in Maccini and Yang (2009), selection in the sample of children due to differential survival might bias the results. This would arise if the most affected children had died before being surveyed and, therefore, the observed children would be an already selected sample of relatively stronger people. To test if selection is present, we show that tropical storms have no relationship with the children's likelihood of appearing in the survey. That is, we find null relationship between the storms' strength and the size of birth cohorts by district-year-season (results available upon request).

Fifth, if our results are real and are not simply reflecting a random occurrence, there should not be any relationship between our outcomes and storms not yet suffered. To test for this, we regress the outcome variables on future storms (two and three years after the real gestation period) as if they had occurred during the gestation period. Appendix Tables 4–6 show that less than 10 percent of all estimated parameters in these placebo tests were statistically significant at the 10 percent level or lower.[16] This provides further confidence that our results are not just driven by random chance.

Sixth, our results assume that the district where the household resided on the interview date was also the district where it resided during the pregnancy. Therefore, it is important to show that internal migration is not biasing the results. Since the SLC interviews a sub-sample of the April LFS and, as shown in Appendix 1, the LFS contains a rotating panel component; then it is possible to identify a household-level panel in the SLC. We label this as a panel "by-chance" since the SLC per se has no panel component but rather is a random subsample of the LFS (which does have a panel component). This enabled us to identify 292 cases where we observed the mother while she was pregnant and in at least one subsequent period after the child was born.[17] For these cases, we know the exact location (i.e., the district) where the mother resided during pregnancy.

As such, to test possible biases due to migration, we implemented a bounds approach. This consisted of imputing two extreme levels of outcome values to the individuals whose mothers we do not observe during the pregnancy period. If the estimation results combining the imputed values for the non-panel individuals while using the actual outcomes for the panel individuals show the same sign as the results without imputation, then we can be more confident that potential internal migration is not biasing the results. We implement these estimations with two alternative imputations of extreme values: the 10th–90th and the 25th–75th percentiles of the outcome distribution of panel individuals. Results shown in Appendix Tables 7–9 reject in general the hypothesis that the point estimates found are zero.

In addition, using data from the Population Census of Jamaica in 2001 and 2011, we found that migration across parishes for children under 5 is low. In 2001, the percentage of children under 5 who were born in a different parish than the current parish of residency was 9 percent, for children under 4 it was 8.4 percent, for children under 3 it was 7.7 percent, for children under 2 it was 6.8 percent, and for children under one year old it was 5.7 percent. The figures from the 2011 census were 8.45 percent, 7.9 percent, 7.2 percent, 6.3 percent, and 5.3 percent, respectively.

Finally, it could be that our results were not the effects of storms suffered during pregnancy, but rather a reflection of the presence (or absence) of interventions that would

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[16] Specifically, Appendix Table 4 contains six estimated parameters statistically significant out of 60, Appendix Table 5 contains five out of 60, and Appendix Table 6 contains six out of 60.

[17] For this exercise, we focused on survey rounds starting from 2002 onward. This is because information regarding the mother of each child surveyed was not collected before 2002.

have responded to storms in post-pregnancy periods. For example, if the advent of a storm during pregnancy had triggered a scarcity of vaccinations received within the first moments of life, then our results in terms of anthropometric measurements could be reflecting this. To test for this, we estimate model (3) having an indicator for whether the child received the bacille Calmette-Guerin (bcg) vaccination that is supposed to be received at birth. The results (available upon request) were all insignificant, suggesting that this channel is unlikely to be pervasive.

8. Conclusion

We studied the effects of tropical storms and hurricanes experienced during pregnancy on birth weight and children's physical development within the first 60 months of life. Using variation in the storms' destructive power between 1987 and 2011 at the district level coupled with anthropometric measurements taken at the household level, we find evidence of nonlinear effects. When tropical storms and one average hurricane hit within the second trimester of pregnancy, some positive effects are found in birth weight as well as ZWH and ZWA standardised measures. However, when destruction indexes equivalent to at least two average hurricanes hit while pregnant, serious negative effects occur. Indeed, expectant mothers living in coastal-rural areas exposed to these shocks during their second trimester of pregnancy are 56 percentage points more likely to deliver a baby with low birth weight. In addition, this exposure during the third trimester of pregnancy causes a reduction in children's ZWA (ZWH) measured within the first 60 months of life, equivalent to 1.88 (1.4) standard deviations. Finally, for extreme events located at the top 5 percent of the destruction measure distribution, effects flatten out and sometimes even turn positive.

The nonlinearity of our results is in line with previous findings: (i) The overlapping between tropical storms and rain may boost agricultural output, implying better nutrition (through an increase in crop quantity or income), benefiting children in the womb through the mothers' nutrition (in the spirit of Maccini and Yang, 2009). Aggregate data on agricultural output provided empirical support for this possibility. (ii) A medium to large event would generate stress to pregnant mothers and/or malnourishment due to infrastructure destruction and/or loss of agricultural output, creating an adverse environment for normal fetal development (Camacho, 2008). This is reflected in the negative effects that we document for events related to the combination of two average hurricanes. (iii) A boost in public expenditure and an increase in aid and humanitarian relief funds in the aftermath of an unusually catastrophic event may increase nutrition intake immediately after the storm (Frankenberg, Friedman, and Ingwersen, 2013).

Although no consensus exists, climate change would imply a new tropical storm pattern.[18] Rising sea levels and humidity in the tropical region are critical factors that would exacerbate the destructiveness of storms in coastal areas. Adaptation and resilience to the potential new pattern of events by governments and civil society are, therefore, important.

From a policy perspective, our findings suggest harmful effects of negative shocks suffered in utero on birth weight and early physical development, which have been shown to be correlated in the longer term with adult productivity. Therefore, our results provide additional objective justification for considering policies aimed at protecting expectant mothers at risk of suffering environmental shocks. Policy options toward effectively coping with these risks include weather insurance schemes, food security policies, community bounding strategies, and initiatives that promote resilience and adaptability to climate change, among others.

Beyond our specific results, poverty-related vulnerability will likely increase the potential negative effects of storms. Hallagate et al. (2015) suggest that economic vulnerabilities might create more pronounced poverty traps due to climate change since the poor will not have enough tools to cope with this risk.[19] Informal settlements, insecure sources of income, and inadequate formal insurance will make it impossible for this population to overcome the negative effects of environmental shocks. Public policy discussions on unemployment insurance, improving access to public health and pregnancy checkups, and boosting conditional cash transfer programs could be a good start to think about precautionary measures to confront weather shocks of the magnitude studied in this paper.

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[18] Recently, a discussion by the Geophysical Fluid Dynamic Laboratory, a division of NOAA, has affirmed the existence of a relationship between global warming and the potential increase of stronger cyclones by the end of the century. This will become a clear relationship between climate change and the increase in the risk due to weather shocks.

[19] The document is open to access and can be downloaded from https://openknowledge.worldbank.org/handle/10986/22787

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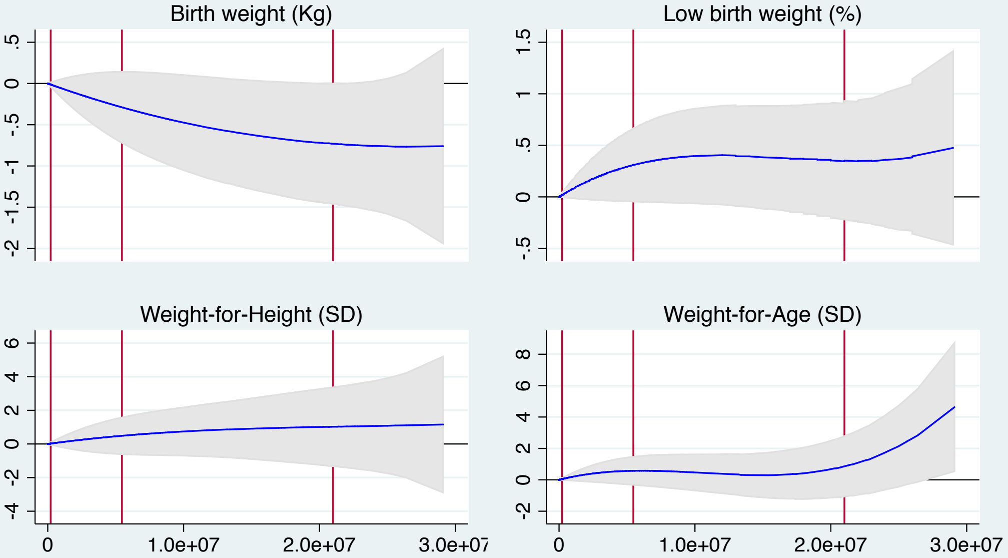
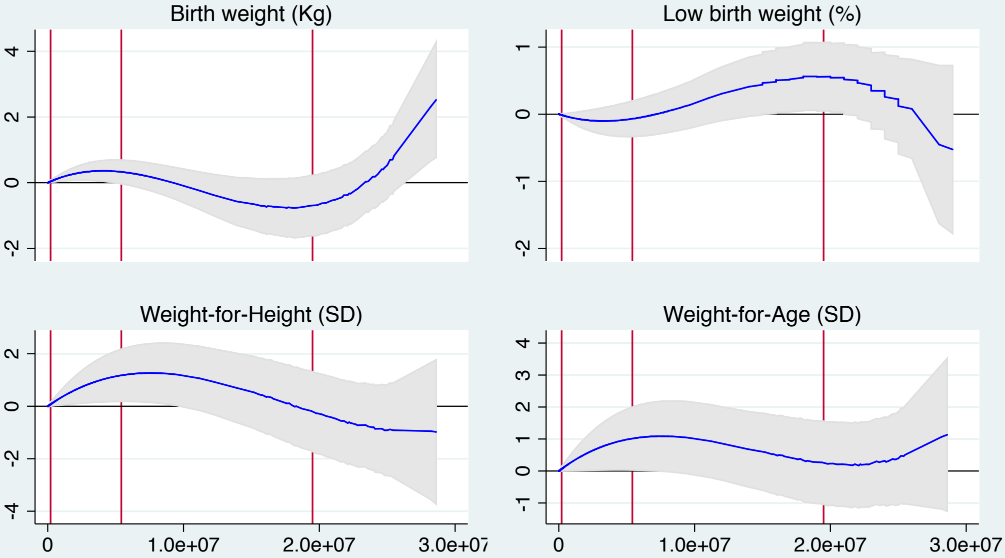
Figure 1: Estimated effects - 1st trimester of gestation



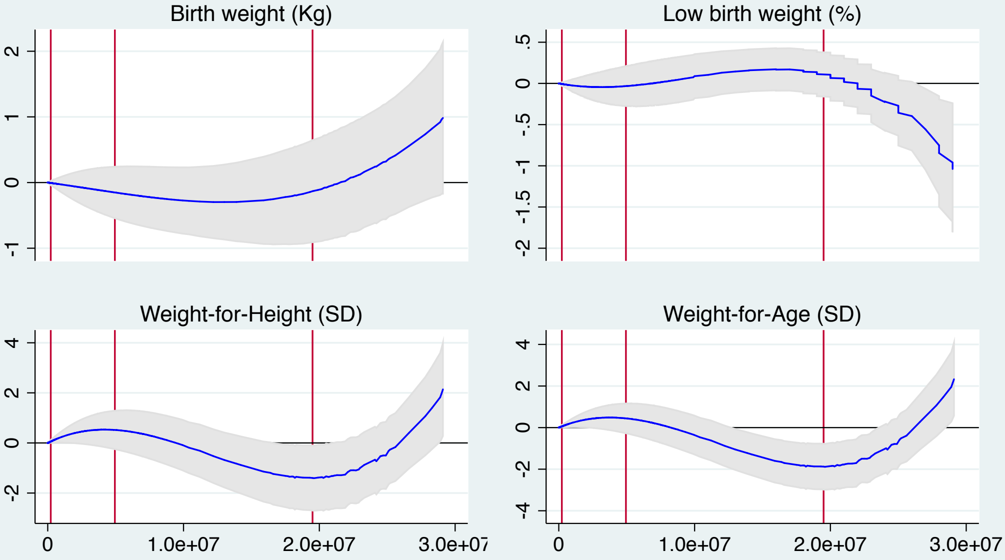
Simulation estimated coefficients in solid blue lines. 90 percent confidence intervals in shaded area.
The X-axis is the destruction measure. The first vertical line is equivalent to an average tropical storm;
the second line is equivalent to an average hurricane;
the third line is equivalent to the combination of two average hurricanes.

Figure 2: Estimated effects - 2nd trimester of gestation



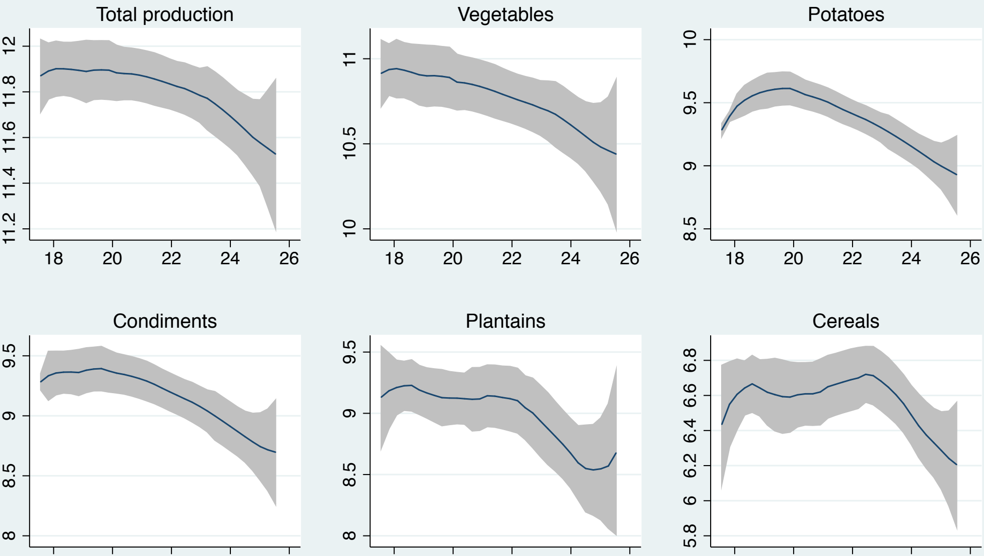
Simulation estimated coefficients in solid blue lines. 90 percent confidence intervals in shaded area.
The X-axis is the destruction measure. The first vertical line is equivalent to an average tropical storm;
the second line is equivalent to an average hurricane;
the third line is equivalent to the combination of two average hurricanes.

Figure 3: Estimated effects - 3rd trimester of gestation



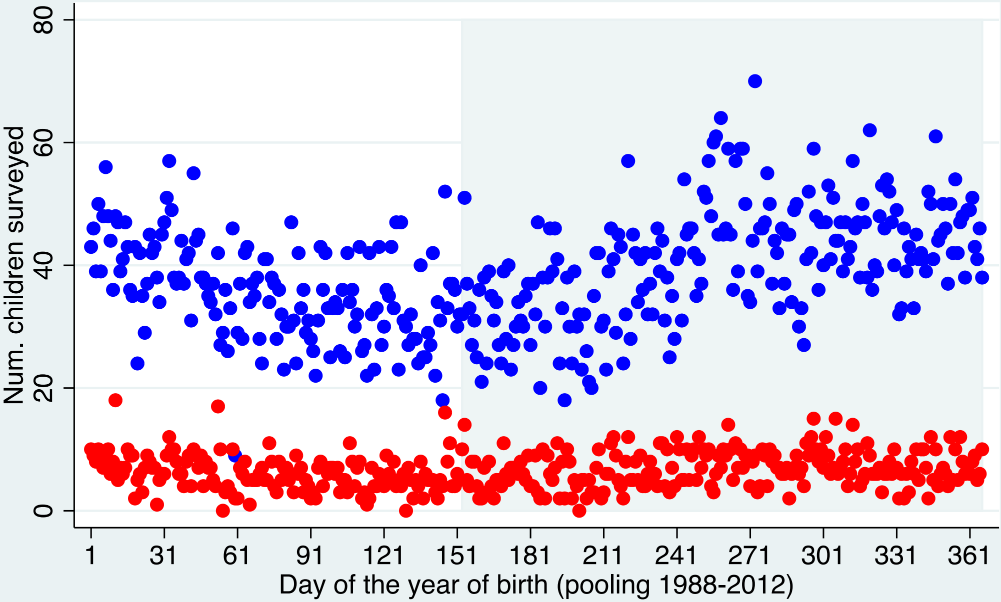
Simulation estimated coefficients in solid blue lines. 90 percent confidence intervals in shaded area.
The X-axis is the destruction measure. The first vertical line is equivalent to an average tropical storm;
the second line is equivalent to an average hurricane;
the third line is equivalent to the combination of two average hurricanes.

Figure 4: Kernel regressions.
log(crop production) Vs. log (destruction variable)



Kernel regressions estimates in solid blue. 90 percent confidence interval in shade region
Y-axis representes produced crop in log(tons). X-axis is the log of destruction measure.

Figure 5: Distribution of births by day of the year



In blue is the number of observed children from the complete sample.
In red are the number of children observed in coast rural sample.
The shaded region corresponds to the storms' season (June-December)

Table 1. Descriptive Statistics

Variables	Complete sample	Coast-rural	Difference
Education of household head			
Primary	0.33	0.34	-0.01
	(0.46)	(0.47)	(0.01)
	13447	2459	
Secondary incomplete	0.29	0.29	-0.001
	(0.45)	(0.45)	(<0.01)
	13447	2459	
Secondary	0.33	0.34	-0.003
	(0.47)	(0.47)	(0.01)
	13447	2459	
Tertiary	0.06	0.04	0.01 ***
	(0.22)	(0.19)	(<0.01)
	13447	2459	
Age of household head	43.41	43.40	0.01
	(15.4)	(15.4)	(0.33)
	14109	2569	
Female household head	0.54	0.53	0.01
	(0.49)	(0.49)	(0.01)
	14111	2569	
Household size	6.26	6.13	0.13 **
	(3.09)	(2.72)	(0.06)
	14111	2569	
Children's characteristics			
Age in months	30.12	30.02	0.10
	(16.8)	(16.7)	(0.36)
	14111	2569	
Girl	0.50	0.50	-0.01
	(0.50)	(0.50)	(0.01)
	14111	2569	
Health outcomes			
Birth weight (Kg.)	3.18	3.18	0.0008
	(0.45)	(0.47)	(0.01)
	10468	1840	
Low birth weight	0.08	0.11	-0.02 ***
	(0.28)	(0.31)	(<0.01)
	10468	1840	
Weight-for-Height	0.27	0.22	0.05 *
	(1.20)	(1.18)	(0.02)
	11792	2139	
Weight-for-Age	0.23	0.24	-0.02
	(1.22)	(1.21)	(0.02)
	12573	2279	
Height-for-Age	0.13	0.20	-0.07 **
	(1.41)	(1.38)	(0.03)
	12443	2251	
Vaccines			
bcg	0.89	0.89	0.01
	(0.30)	(0.31)	(<0.01)
	13340	2403	
measles	0.68	0.67	0.01
	(0.46)	(0.47)	(0.01)
	14111	2569	
opv	0.59	0.58	0.01
	(0.49)	(0.49)	(0.01)
	14111	2569	
dtp	0.60	0.61	-0.003
	(0.48)	(0.48)	(0.01)
	14111	2569	
Complete vaccination	0.57	0.56	0.01
	(0.49)	(0.49)	(0.01)
	14111	2569	

Each cell reports: mean, standard deviation in parentheses, and sample size. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Table 2. Average tropical storm's effect on children's health outcomes (exclude hurricanes)- Complete sample

Gestation period	Birth weight	Low birth weight	ZWH	ZWA	ZHA
1st Trimester	-0.003	0.005	0.007	0.01	0.02
	(0.006)	(0.004)	(0.015)	(0.01)	(0.017)
2nd Trimester	0.006	-0.003	0.01	0.005	0.001
	(0.005)	(0.004)	(0.015)	(0.01)	(0.01)
3rd Trimester	0.002	-0.004	0.009	0.004	0.006
	(0.005)	(0.003)	(0.013)	(0.01)	(0.01)
Observations	*9963*	*9963*	*11255*	*11991*	*11864*

Notes: This table present the results from the estimation of equation 3 using the complete sample. All the regressions include controls and fixed effects for birth year-month, survey year, district, and district-birth year-specific linear time trend. Controls included are: household head's education and age and a dummy for female head, household size, number of individuals in household of age 0-5, 6-14, 15-24, 25-49, and child's age and gender. Birth weight in kilograms, low birth weight is a dummy equals to one if birth weight is lower than 2.5 kilograms, and z- scores are measured in standard deviations. Estimated standard errors, reported in parentheses, are clustered at the district level. Values for simulation were 215500 for Q1, 211261 for Q2, and 224532 for Q3 corresponding from average destruction due to the impact of non hurricane storms in the period. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Table 3. Average tropical storm's effect on children's health outcomes (exclude hurricanes)- Coast-Rural

Gestation period	Birth weight	Low birth weight	ZWH	ZWA	ZHA
1st Trimester	-0.01	0.02	0.02	0.04	0.04
	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)
2nd Trimester	0.04**	-0.01	0.08*	0.07*	0.003
	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)
3rd Trimester	-0.01	-0.006	0.06*	0.06**	-0.01
	(0.01)	(0.01)	(0.03)	(0.02)	(0.03)
Observations	*1764*	*1764*	*2052*	*2186*	*2159*

Notes: This table present the results from the estimation of equation 3 using the coast rural sample. All the regressions include controls and fixed effects for birth year-month, survey year, district, and district-birth year-specific linear time trend. Controls included are: household head's education and age and a dummy for female head, household size, number of individuals in household of age 0-5, 6-14, 15-24, 25-49, and child's age and gender (dummy for female). Birth weight in kilograms, low birth weight is a dummy equals to one if birth weight is lower than 2.5 kilograms, and z- scores are measured in standard deviations. Estimated standard errors, reported in parentheses, are clustered at the district level. Values for simulation were 215500 for Q1, 211261 for Q2, and 224532 for Q3 corresponding from average destruction due to the impact of non hurricane storms in the period. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Table 4. Average storm's effect on children's health outcomes when hit by at most one hurricane - Complete sample

Gestation period	Birth weight	Low birth weight	ZWH	ZWA	ZHA
1st Trimester	-0.03	0.07	0.06	0.10	0.26
	(0.07)	(0.06)	(0.19)	(0.18)	(0.20)
2nd Trimester	0.05	0.004	0.16	0.04	0.02
	(0.07)	(0.05)	(0.19)	(0.19)	(0.20)
3rd Trimester	0.01	-0.02	0.08	0.01	0.04
	(0.06)	(0.04)	(0.16)	(0.14)	(0.16)
Observations	*9963*	*9963*	*11255*	*11991*	*11864*

Notes: This table present the results from the estimation of equation 3 using the complete sample. All the regressions include controls and fixed effects for birth year-month, survey year, district, and district-birth year-specific linear time trend. Controls included are: household head's education and age and a dummy for female head, household size, number of individuals in household of age 0-5, 6-14, 15-24, 25-49, and child's age and gender (dummy for female). Birth weight in kilograms, low birth weight is a dummy equals to one if birth weight is lower than 2.5 kilograms, and z- scores are measured in standard deviations. Estimated standard errors, reported in parentheses, are clustered at the district level. Values for simulation were 5.4 mill. for Q1 and Q2, and 4.9 mill. for Q3 corresponding from median destruction due to the impact of at most one hurricanes in the period. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Table 5. Average storm's effect on children's health outcomes when hit by at most one hurricane - Coast-Rural

Gestation period	Birth weight	Low birth weight	ZWH	ZWA	ZHA
1st Trimester	-0.18	0.30	0.31	0.46	0.35
	(0.17)	(0.21)	(0.17)	(0.17)	(0.17)
2nd Trimester	0.35**	-0.08	0.91**	0.79*	0.08
	(0.17)	(0.15)	-0.17	(0.17)	(0.17)
3rd Trimester	-0.12	-0.03	0.53	0.48	-0.18
	(0.17)	(0.15)	(0.17)	(0.17)	(0.17)
Observations	*1764*	*1764*	*2052*	*2186*	*2159*

Notes: This table present the results from the estimation of equation 3 using the coast rural sample. All the regressions include controls and fixed effects for birth year-month, survey year, district, and district-birth year-specific linear time trend. Controls included are: household head's education and age and a dummy for female head, household size, number of individuals in household of age 0-5, 6-14, 15-24, 25-49, and child's age and gender (dummy for female). Birth weight in kilograms, low birth weight is a dummy equals to one if birth weight is lower than 2.5 kilograms, and z- scores are measured in standard deviations. Estimated standard errors, reported in parentheses, are clustered at the district level. Values for simulation were 5.4 mill. for Q1 and Q2, and 4.9 mill. for Q3 corresponding from median destruction due to the impact of at most one hurricanes in the period. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Table 6. Average storm's effect on children's health outcomes when hit by two or more hurricanes - Complete sample

Gestation period	Birth weight	Low birth weight	ZWH	ZWA	ZHA
1st Trimester	-0.22	0.10	-0.22	-0.08	0.56
	(0.40)	(0.1)	(0.40)	(0.41)	(0.42)
2nd Trimester	-0.12	0.2*	-0.12	-0.08	0.32
	(0.39)	(0.11)	(0.39)	(0.36)	(0.37)
3rd Trimester	-0.16	0.17**	-0.16	-0.29	-0.31
	(0.33)	(0.08)	(0.33)	(0.31)	(0.32)
Observations	*9963*	*9963*	*11255*	*11991*	*11864*

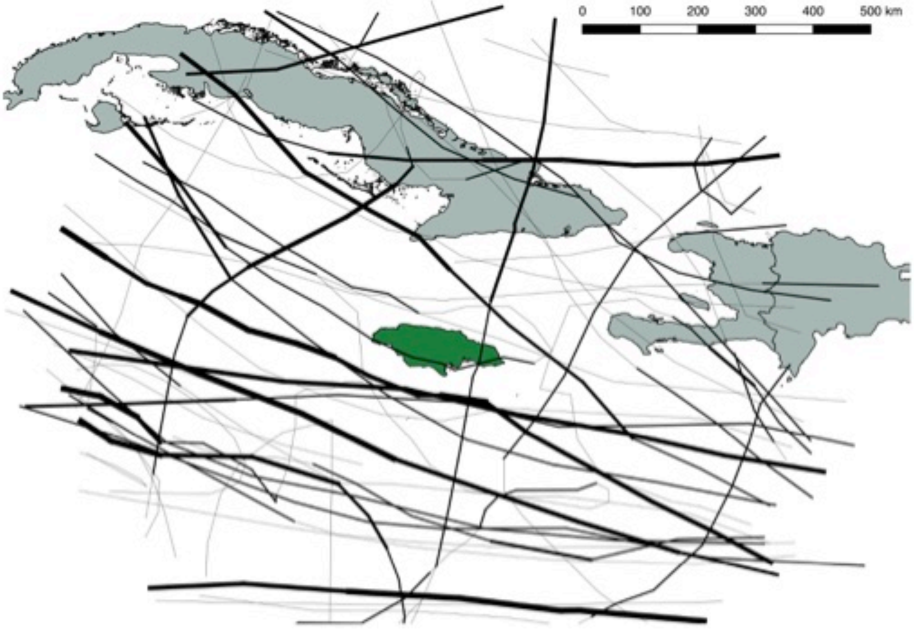
Notes: This table present the results from the estimation of equation 3 using the complete sample. All the regressions include controls and fixed effects for birth year-month, survey year, district, and district-birth year-specific linear time trend. Controls included are: household head's education and age and a dummy for female head, household size, number of individuals in household of age 0-5, 6-14, 15-24, 25-49, and child's age and gender (dummy for female). Birth weight in kilograms, low birth weight is a dummy equals to one if birth weight is lower than 2.5 kilograms, and z- scores are measured in standard deviations. Estimated standard errors, reported in parentheses, are clustered at the district level. Values for simulation were 21 mill. for Q1 and Q2 and 19.5 mill. for Q3 corresponding from median destruction due to the impact of two or more hurricanes in the same period. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Table 7. Average storm's effect on children's health outcomes when hit by two or more hurricanes - Coast-Rural

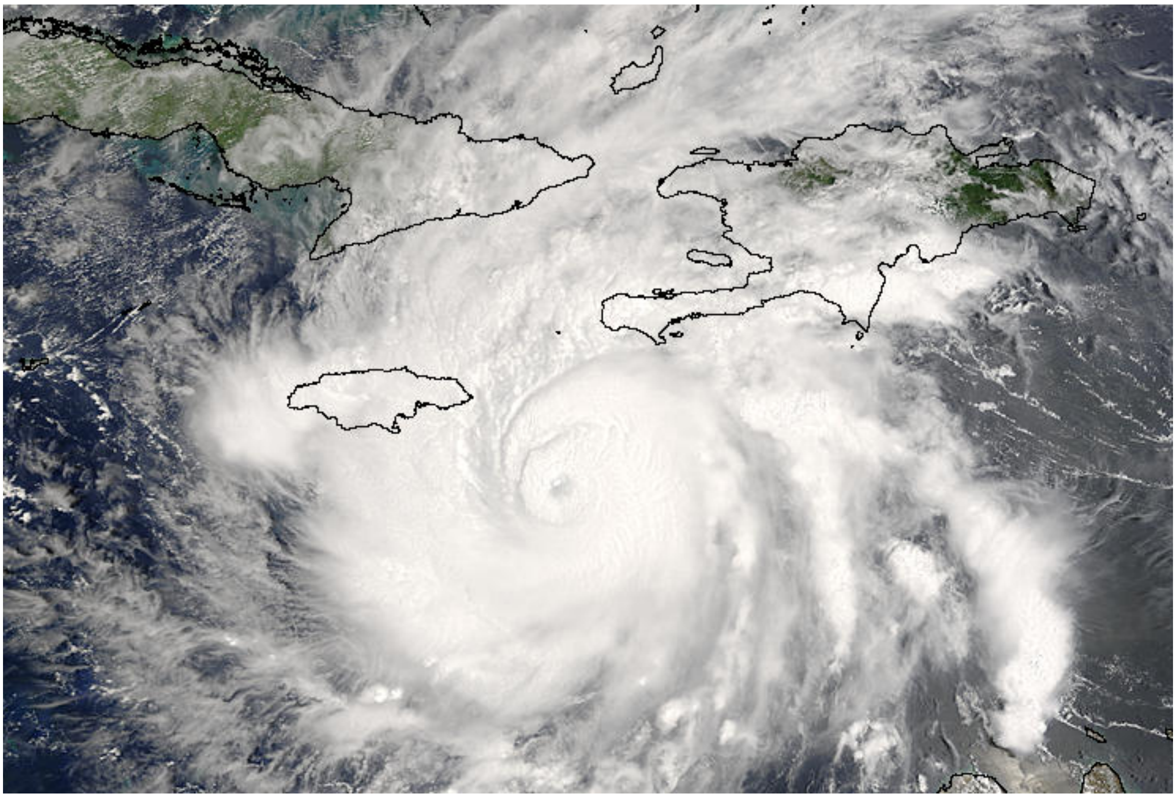
Gestation period	Birth weight	Low birth weight	ZWH	ZWA	ZHA
1st Trimester	-0.73*	0.35	1.02	0.86	0.5
	(0.44)	(0.34)	(1.41)	(1.16)	(1.22)
2nd Trimester	-0.7	0.56*	-0.21	0.25	1.09
	(0.55)	(0.31)	(0.92)	(0.78)	(0.92)
3rd Trimester	-0.13	0.11	-1.4*	-1.88***	-0.52
	(0.47)	(0.16)	(0.78)	(0.66)	(0.93)
Observations	*1764*	*1764*	*2052*	*2186*	*2159*

Notes: This table present the results from the estimation of equation 3 using the coast rural sample. All the regressions include controls and fixed effects for birth year-month, survey year, district, and district-birth year-specific linear time trend. Controls included are: household head's education and age and a dummy for female head, household size, number of individuals in household of age 0-5, 6-14, 15-24, 25-49, and child's age and gender (dummy for female). Birth weight in kilograms, low birth weight is a dummy equals to one if birth weight is lower than 2.5 kilograms, and z- scores are measured in standard deviations. Estimated standard errors, reported in parentheses, are clustered at the district level. Values for simulation were 21 mill. for Q1 and Q2 and 19.5 mill. for Q3 corresponding from median destruction due to the impact of two or more hurricanes in the same period. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Appendix Figure 1. Set of Storms



1.a. The distribution across the space of the storms in sample studied.
Source: NOAA IBTrACS, own calculations



1.b. Hurricane Ivan in 2004 approaching Jamaica.
Source: https://visibleearth.nasa.gov/view.php?id=71977. Visited August 17th, 2017

Appendix Table 1. Storms' set used in the analysis

Year	Storm	Max wind speed (Km/h)	Start date (near to Jamaica)	End date (near to Jamaica)	Saffir–Simpson Scale
1987	UNNAMED	30	6-Sep-87	8-Sep-87	TD
1987	EMILY	110	20-Sep-87	26-Sep-87	TS
1987	FLOYD	65	9-Oct-87	13-Oct-87	TS
1987	UNNAMED	30	31-Oct-87	4-Nov-87	TD
1988	SIX:UNNAMED	30	20-Aug-88	24-Aug-88	TD
1988	CHRIS	45	21-Aug-88	30-Aug-88	TD
1988	GILBERT	160	8-Sep-88	19-Sep-88	SS 2
1988	KEITH	65	17-Nov-88	26-Nov-88	TS
1990	ARTHUR	60	22-Jul-90	27-Jul-90	TD
1990	MARCO	55	9-Oct-90	13-Oct-90	TD
1994	GORDON	75	8-Nov-94	21-Nov-94	TS
1995	ROXANNE	100	7-Oct-95	20-Oct-95	TS
1996	DOLLY	70	19-Aug-96	24-Aug-96	TS
1996	LILI	100	14-Oct-96	28-Oct-96	TS
1996	MARCO	65	13-Nov-96	26-Nov-96	TS
1998	GEORGES	135	15-Sep-98	1-Oct-98	SS 1
1998	MITCH	155	22-Oct-98	9-Nov-98	SS 2
1999	IRENE	95	12-Oct-99	19-Oct-99	TS
1999	LENNY	135	13-Nov-99	23-Nov-99	SS 1
2000	DEBBY	75	19-Aug-00	24-Aug-00	TS
2000	HELENE	60	15-Sep-00	25-Sep-00	TD
2001	CHANTAL	60	14-Aug-01	22-Aug-01	TD
2001	IRIS	125	4-Oct-01	9-Oct-01	SS 1
2002	ISIDORE	110	14-Sep-02	27-Sep-02	TS
2002	LILI	125	21-Sep-02	4-Oct-02	SS 1
2002	UNNAMED	30	14-Oct-02	16-Oct-02	TD
2003	CLAUDETTE	80	7-Jul-03	17-Jul-03	TS
2003	ODETTE	55	4-Dec-03	9-Dec-03	TD
2004	BONNIE	55	3-Aug-04	13-Aug-04	TD
2004	CHARLEY	130	9-Aug-04	15-Aug-04	SS 1
2004	IVAN	145	2-Sep-04	24-Sep-04	SS 1
2004	JEANNE	105	13-Sep-04	29-Sep-04	TS
2005	ALPHA	45	22-Oct-05	24-Oct-05	TD
2005	DENNIS	130	4-Jul-05	18-Jul-05	SS 1
2005	EMILY	140	11-Jul-05	21-Jul-05	SS 1
2005	GAMMA	45	14-Nov-05	21-Nov-05	TD
2005	WILMA	160	15-Oct-05	26-Oct-05	SS 2
2006	CHRIS	55	1-Aug-06	6-Aug-06	TD
2006	ERNESTO	75	24-Aug-06	4-Sep-06	TS
2007	DEAN	150	13-Aug-07	22-Aug-07	SS 1
2007	FELIX	150	31-Aug-07	6-Sep-07	SS 1
2007	NOEL	75	24-Oct-07	5-Nov-07	TS
2007	OLGA	50	10-Dec-07	16-Dec-07	TD
2008	FAY	60	15-Aug-08	28-Aug-08	TD
2008	GUSTAV	135	25-Aug-08	5-Sep-08	SS 1
2008	HANNA	75	28-Aug-08	8-Sep-08	TS
2008	IKE	125	1-Sep-08	15-Sep-08	SS 1
2008	PALOMA	125	5-Nov-08	14-Nov-08	SS 1
2010	ALEX	95	24-Jun-10	1-Jul-10	TS
2010	BONNIE	40	22-Jul-10	25-Jul-10	TD
2010	KARL	110	13-Sep-10	18-Sep-10	TS
2010	MATTHEW	50	23-Sep-10	26-Sep-10	TD
2010	NICOLE	40	28-Sep-10	30-Sep-10	TD
2010	RICHARD	85	19-Oct-10	26-Oct-10	TS
2010	TOMAS	85	29-Oct-10	10-Nov-10	TS
2011	EMILY	45	2-Aug-11	7-Aug-11	TD
2011	RINA	100	22-Oct-11	29-Oct-11	TS
2012	ERNESTO	75	1-Aug-12	10-Aug-12	TS
2012	HELENE	50	9-Aug-12	18-Aug-12	TD
2012	ISAAC	70	20-Aug-12	1-Sep-12	TS
2012	SANDY	100	21-Oct-12	31-Oct-12	TS
2013	DORIAN	50	31-Jul-13	31-Jul-13	TD
2014	HANNA:INVEST	35	25-Oct-14	26-Oct-14	TD

Appendix Table 2. Storms' effects on controls - Coast-Rural

		Household head's education				Household's size					Household head and children's gender and age			
Destruction Received	Gestation period	Primary	Sec. incomplete	Secondary	Tertiary	Total hhs	hhs 0 to 5 years old	hhs 6 to 14 years old	hhs 15 to 24 years old	hhs 25 to 49 years old	Female household head	Age (household head)	Age (children)	Girl
Tropical storm (excld.Hurricanes)	1st Trimester	-0.13	0.1	0.02	0.01	-0.29	0.57	0.82	-0.19	-0.15	0.02	-0.23	-0.03	-0.08
		(0.1)	(0.16)	(0.14)	(0.06)	(0.63)	(0.48)	(0.73)	(0.56)	(0.44)	(0.17)	(4.52)	(0.19)	(0.14)
	2nd Trimester	-0.004	0.002	0.002	-0.0001	-0.1*	-0.08	-0.11	-0.01	-0.06	-0.003	-0.25	0.004	0.001
		(0.008)	(0.01)	(0.01)	(0.01)	(0.06)	(0.06)	(0.09)	(0.07)	(0.04)	(0.01)	(0.42)	(0.02)	(0.01)
	3rd Trimester	-0.04	0.1	-0.04	-0.02	0.42	0.4	0.54	0.22	0.05	0.11*	-3.02	-0.04	-0.01
		(0.04)	(0.06)	(0.05)	(0.03)	(0.34)	(0.26)	(0.34)	(0.29)	(0.24)	(0.06)	(2.07)	(0.11)	(0.07)
	Observations	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*
At most one hurricane	1st Trimester	-0.32*	0.3	0.01	0.01	-0.66	0.24	1.26	-0.58	-0.48	-0.07	0.11	-2	-0.3
		(0.17)	(0.26)	(0.22)	(0.1)	(1.06)	(0.83)	(1.29)	(0.92)	(0.75)	(0.24)	(0.28)	(8.09)	(0.36)
	2nd Trimester	-0.114	0.059	0.048	0.0072	-1.44	-1.34	-1.79	-0.02	-0.9*	-0.009	-0.05	-3.13	0.079
		(0.11)	(0.16)	(0.15)	(0.06)	(0.91)	(0.96)	(1.28)	(0.9)	(0.5)	(0.15)	(0.16)	(5.69)	(0.23)
	3rd Trimester	-0.08	0.24	-0.15	-0.01	1.15	1.11	0.97	0.89	0.08	0.01	0.33*	-3.97	-0.06
		(0.13)	(0.17)	(0.14)	(0.07)	(0.99)	(0.71)	(0.94)	(0.84)	(0.7)	(0.21)	(0.18)	(5.76)	(0.35)
	Observations	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*
Two or more hurricanes	1st Trimester	-0.41**	0.44	0.08	-0.11	0.79	-0.91	1.19	-0.36	-0.47	-0.34	-0.23	0.02	-0.71
		(0.19)	(0.35)	(0.32)	(0.13)	(1.71)	(1.15)	(1.77)	(1.04)	(0.93)	(0.38)	(0.34)	(12.9)	(0.64)
	2nd Trimester	-0.4**	0.374	0.002	0.0195	0.3	-1.35	-2.2	1.33	-0.85	-0.185	0.07	2.409	0.189
		(0.16)	(0.27)	(0.23)	(0.14)	(1.64)	(1.26)	(1.71)	(1.14)	(0.85)	(0.32)	(0.31)	(9.46)	(0.57)
	3rd Trimester	-0.1	0.22	-0.16	0.04	0.08	0.6	-0.85	1.12	-0.25	-0.02	0.34	2.8	-0.3
		(0.13)	(0.19)	(0.18)	(0.07)	(1.22)	(0.75)	(1.21)	(0.82)	(0.73)	(0.34)	(0.22)	(7.28)	(0.45)
	Observations	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*	*2569*

Notes: This table presents the test on covariates using the specification described in equation 3. All the regressions include controls and fixed effects for birth year-month, survey year, district, and district-birth year-specific linear time trend. The selected sample is children living in rural-coast area and the estimated standard errors, reported in parentheses, are clustered at the district level. Values for simulation on tropical storm were 215500 for Q1, 211261 for Q2, 224532 for Q3 and 256540 gestation corresponding from destruction due to the impact of non hurricane storms in the period. Values for simulation on one hurricane were 5.4 mill. for Q1 and Q2, 4.9 mill. for Q3 and 5.3mill. Values for simulation on on more than one hurricane were 21 mill. for Q1 and Q2 and 19.5 mill. for Q3 and gestation corresponding from average destruction due to the impact of two or more hurricanes in the same period. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Appendix Table 3. Adaptability measured as change in house outer walls' quality

Destruction Received	Outcome variable: indicator of good quality walls.						
Average tropical storm (excld. Hurricanes)	12 month Storm	0.000	0.022	0.025	0.015	0.011	0.011
		(0.042)	(0.042)	(0.042)	(0.042)	(0.043)	(0.043)
At most one hurricane	12 month Storm	0.000	0.011	0.013	0.008	0.005	0.006
		(0.021)	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)
Two or more hurricanes	12 month Storm	0.066	0.109	0.126	0.116	0.101	0.098
		(0.125)	(0.140)	(0.145)	(0.143)	(0.144)	(0.146)
Controls	Education controls	No	Yes	Yes	Yes	Yes	Yes
	Head's age	No	No	Yes	Yes	Yes	Yes
	Household's size controls	No	No	No	Yes	Yes	Yes
	Children's age	No	No	No	No	Yes	Yes
	Children and head's gender	No	No	No	No	No	Yes
Observations		*2401*	*2292*	*2292*	*2292*	*2292*	*2292*

Notes: This table present the results on the test for adaptation to storms. The outcome variable is a dummy equal to one if material used to build walls is brick, concrete nog, or concrete, and zero otherwise All the regressions include fixed effects for birth year-month, survey year, district, and district-birth year-specific linear time trend. Values for simulation on tropical storm were 215500 for Q1, 211261 for Q2, 224532 for Q3 and 256540 gestation corresponding from destruction due to the impact of non hurricane storms in the period. Values for simulation on one hurricane were 5.4 mill. for Q1 and Q2, 4.9 mill. for Q3 and 5.3mill. Values for simulationon on more than one hurricane were 21 mill. for Q1 and Q2 and 19.5 mill. for Q3 and gestation corresponding from average destruction due to the impact of two or more hurricanes in the same period. The selected sample is households with children age 0 to 5 years old living in rural-coast area. Estimated standard errors, reported in parentheses, are clustered at the district level. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Appendix Table 4. Placebo test average destruction due to average tropical storm

		Assuming storms hit two years after measurement					Assuming storms hit three years after measurement				
Sample	Gestation period	Birth weight	Low birth weight	ZWH	ZWA	ZHA	Birth weight	Low birth weight	ZWH	ZWA	ZHA
Coast rural sample	1st Trimester	-0.008	-0.001	-0.009	0.03	0.003	0.001	-0.002	-0.005	-0.02	-0.01
		(0.03)	(0.02)	(0.07)	(0.06)	(0.08)	(0.008)	(0.003)	(0.01)	(0.02)	(0.02)
	2nd Trimester	0.0097	-0.03***	-0.001	0.0004	0.02	0.003	-0.01	-0.33*	-0.18	0.11
		(0.01)	(0.009)	(0.03)	(0.03)	(0.03)	(0.07)	(0.02)	(0.18)	(0.14)	(0.13)
	3rd Trimester	-0.02	0.01	-0.09	-0.15	0.04	0.18*	0.01	-0.07	-0.19	0.08
		(0.11)	(0.06)	(0.11)	(0.12)	(0.18)	(0.1)	(0.07)	(0.28)	(0.26)	(0.36)
	Observations	*1764*	*1764*	*2052*	*2186*	*2159*	*1764*	*1764*	*2052*	*2186*	*2159*
Complete sample	1st Trimester	0.008	-0.007	0.008	0.006	0.01	0.002	-0.004	-0.01	-0.01	0.005
		(0.01)	(0.006)	(0.03)	(0.03)	(0.03)	(0.004)	(0.003)	(0.01)	(0.01)	(0.01)
	2nd Trimester	-0.003	-0.003	-0.009	-0.01	0.003	-0.03	0.02*	-0.16***	-0.13**	-0.08
		(0.007)	(0.004)	(0.01)	(0.01)	(0.02)	(0.02)	(0.012)	(0.05)	(0.05)	(0.06)
	3rd Trimester	-0.00001	-0.0004	0.01	0.01	-0.001	0.01	-0.02	0.07	0.09	0.06
		(0.004)	(0.002)	(0.01)	(0.02)	(0.02)	(0.05)	(0.03)	(0.13)	(0.13)	(0.15)
	Observations	*9963*	*9963*	*11255*	*11991*	*11864*	*9963*	*9963*	*11255*	*11991*	*11864*

Notes: This table presents the results for the placebo test using the equation 3. All the regressions include controls and fixed effects for birth year-month, survey year, district, and district-birth year-specific linear time trend. Controls included are: household head's education and age and a dummy for female head, household size, number of individuals in household of age 0-5, 6-14, 15-24, 25-49, and child's age and gender (dummy for female). The selected sample is children living in rural-coast area and the estimated standard errors, reported in parentheses, are clustered at the district level. Values for simulation were 21 mill. for Q1 and Q2 and 19.5 mill. for Q3 and gestation corresponding from median destruction due to the impact of two or more hurricanes in the same period. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Appendix Table 5. Placebo test average destruction due to at most one hurricane

		Assuming storms hit two years after measurement					Assuming storms hit three years after measurement				
Sample	Gestation period	Birth weight	Low birth weight	ZWH	ZWA	ZHA	Birth weight	Low birth weight	ZWH	ZWA	ZHA
Coast rural sample	1st Trimester	-0.34	-0.02	-0.26	-0.45	-0.76	-0.06	-0.05	-0.15	-0.85	-0.42
		(0.31)	(0.2)	(0.66)	(0.59)	(0.82)	(0.34)	(0.13)	(0.58)	(0.93)	(1.02)
	2nd Trimester	0.1	-0.32***	-0.02	-0.04	0.15	0.03	-0.03	-1.56**	-0.98	0.38
		(0.16)	(0.11)	(0.36)	(0.31)	(0.43)	(0.29)	(0.1)	(0.77)	(0.64)	(0.59)
	3rd Trimester	-0.05	0.02	-0.26	-0.44	0.1	0.02*	0.0002	-0.01	-0.01	0.02
		(0.31)	(0.18)	(0.31)	(0.35)	(0.53)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
	Observations	*1764*	*1764*	*2052*	*2186*	*2159*	*1764*	*1764*	*2052*	*2186*	*2159*
Complete sample	1st Trimester	-0.03	-0.05	-0.01	-0.02	0.003	0.02	-0.13	-0.43	-0.4	0.1
		(0.1)	(0.06)	(0.22)	(0.24)	(0.31)	(0.14)	(0.09)	(0.36)	(0.36)	(0.49)
	2nd Trimester	-0.03	-0.03	-0.07	-0.09	0.02	-0.09	0.07	-0.66***	-0.51**	-0.25
		(0.07)	(0.04)	(0.15)	(0.14)	(0.18)	(0.08)	(0.05)	(0.21)	(0.22)	(0.23)
	3rd Trimester	-0.001	-0.003	0.09	0.04	-0.01	0.001	-0.001	0.001	0.002	0.002
		(0.03)	(0.02)	(0.11)	(0.13)	(0.13)	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)
	Observations	*9963*	*9963*	*11255*	*11991*	*11864*	*9963*	*9963*	*11255*	*11991*	*11864*

Notes: This table presents the results for the placebo test using the equation 3. All the regressions include controls and fixed effects for birth year-month, survey year, district, and district-birth year-specific linear time trend. Controls included are: household head's education and age and a dummy for female head, household size, number of individuals in household of age 0-5, 6-14, 15-24, 25-49, and child's age and gender (dummy for female). The selected sample is children living in rural-coast area and the estimated standard errors, reported in parentheses, are clustered at the district level. Values for simulation were 5.4 mill. for Q1 and Q2, 4.9 mill. for Q3 and 5.3mill. gestation corresponding from median destruction due to the impact of at most one hurricanes in the period. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Appendix Table 6. Placebo test average destruction due to two or more hurricanes

		Assuming storms hit two years after measurement					Assuming storms hit three years after measurement				
Sample	Gestation period	Birth weight	Low birth weight	ZWH	ZWA	ZHA	Birth weight	Low birth weight	ZWH	ZWA	ZHA
Coast rural sample	1st Trimester	-0.48	-0.26	-0.52	-1.12	-1.24	-0.63*	0.2	0.46	0.3	-0.39
		(0.48)	(0.26)	(0.71)	(0.74)	(1.01)	(0.37)	(0.19)	(0.69)	(1.03)	(1.2)
	2nd Trimester	0.09	-0.26***	-0.02	-0.02	0.14	-0.01	-0.05	-1.09*	-1.89**	-0.78
		(0.13)	(0.09)	(0.29)	(0.26)	(0.35)	(0.42)	(0.2)	(0.65)	(0.83)	(1)
	3rd Trimester	-0.05	0.02	-0.26	-0.44	0.1	0.02*	0.0002	-0.01	-0.01	0.02
		(0.31)	(0.18)	(0.31)	(0.35)	(0.53)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
	Observations	1764	1764	2052	2186	2159	1764	1764	2052	2186	2159
Complete sample	1st Trimester	-0.1	-0.05	-0.07	0.02	-0.09	-0.2	-0.04	0.29	-0.07	-0.25
		(0.16)	(0.09)	(0.35)	(0.39)	(0.52)	(0.14)	(0.08)	(0.29)	(0.35)	(0.42)
	2nd Trimester	-0.03	-0.02	-0.06	-0.08	0.02	0.03	-0.08	-0.81**	-0.67	0.13
		(0.05)	(0.03)	(0.12)	(0.11)	(0.14)	(0.15)	(0.11)	(0.41)	(0.44)	(0.57)
	3rd Trimester	-0.001	-0.003	0.09	0.04	-0.01	0.001	-0.001	0.001	0.002	0.002
		(0.03)	(0.02)	(0.11)	(0.13)	(0.13)	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)
	Observations	9963	9963	11255	11991	11864	9963	9963	11255	11991	11864

Notes: This table presents the results for the placebo test using the equation 3. All the regressions include controls and fixed effects for birth year-month, survey year, district, and district-birth year-specific linear time trend. Controls included are: household head's education and age and a dummy for female head, household size, number of individuals in household of age 0-5, 6-14, 15-24, 25-49, and child's age and geneder (dummy for female). The selected sample is children living in rural-coast area and the estimated standard errors, reported in parentheses, are clustered at the district level. Values for simulation were 21 mill. for Q1 and Q2 and 19.5 mill. for Q3 and gestation corresponding from median destruction due to the impact of two or more hurricanes in the same period. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Appendix Table 7. Bound analysis. Using tropical storms only (excluding hurricanes)

Gestation period	Birth weight			Low birth weight			ZWH			ZWA			ZHA		
	10th percentile	P.E	90th percentile	Best	P.E	Worst	10th percentile	P.E	90th percentile	10th percentile	P.E	90th percentile	10th percentile	P.E	90th percentile
1st Trimester	-0.07	-0.17	-0.14	0.13	0.21	0.11	0.31	0.3	0.24	0.44	0.46	0.36	0.43	0.35	0.25
	(0.18)	(0.18)	(0.17)	(0.15)	(0.15)	(0.17)	(0.46)	(0.46)	(0.46)	(0.38)	(0.38)	(0.39)	(0.29)	(0.29)	(0.29)
2nd Trimester	0.04**	0.04**	0.04**	-0.01	-0.01	-0.01	0.07	0.08*	0.07	0.05	0.07*	0.04	-0.003	0.003	0.002
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
3rd Trimester	-0.07	-0.05	-0.06	-0.03	-0.04	0.05	0.29	0.34*	0.35	0.25	0.34*	0.31*	-0.06	-0.07	0.02
	(0.1)	(0.11)	(0.11)	(0.06)	(0.07)	(0.08)	(0.21)	(0.21)	(0.21)	(0.18)	(0.19)	(0.19)	(0.22)	(0.22)	(0.2)
Observations	*1771*	*1764*	*1771*	*1771*	*1764*	*1771*	*2055*	*2052*	*2055*	*2190*	*2186*	*2190*	*2165*	*2159*	*2165*
Clusters	*329*	*329*	*329*	*329*	*329*	*329*	*335*	*335*	*335*	*338*	*338*	*338*	*337*	*337*	*337*
	25th percentile	P.E	75th percentile				25th percentile	P.E	75th percentile	25th percentile	P.E	75th percentile	25th percentile	P.E	75th percentile
1st Trimester	-0.08	-0.17	-0.12				0.29	0.3	0.26	0.43	0.46	0.41	0.35	0.35	0.3
	(0.18)	(0.18)	(0.17)				(0.46)	(0.46)	(0.46)	(0.38)	(0.38)	(0.38)	(0.29)	(0.29)	(0.29)
2nd Trimester	0.04**	0.04**	0.04**				0.07	0.08*	0.07	0.05	0.07*	0.05	-0.003	0.003	0.001
	(0.02)	(0.02)	(0.02)				(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
3rd Trimester	-0.07	-0.05	-0.06				0.3	0.34*	0.33	0.26	0.34*	0.28	-0.03	-0.07	-0.003
	(0.1)	(0.11)	(0.1)				(0.21)	(0.21)	(0.21)	(0.19)	(0.19)	(0.18)	(0.2)	(0.22)	(0.2)
Observations	*1771*	*1764*	*1771*				*2055*	*2052*	*2055*	*2190*	*2186*	*2190*	*2165*	*2159*	*2165*
Clusters	*329*	*329*	*329*				*335*	*335*	*335*	*338*	*338*	*338*	*337*	*337*	*337*

Notes: This table presents the results for the bounds test. All the regressions include controls and fixed effects for birth year-month, survey year, district, and district-birth year-specific linear time trend. Controls included are: household head's education and age and a dummy for female head, household size, number of individuals in household of age 0-5, 6-14, 15-24, 25-49, and child's age and gender (dummy for female). The selected sample is children living in rural-coast area and the estimated standard errors, reported in parentheses, are clustered at the district level. Values for simulation were 215500 for Q1, 211261 for Q2, and 224532 for Q3 corresponding from average destruction due to the impact of non hurricane storms in the period. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Appendix Table 8. Bound analysis. Using destruction due to at most one hurricane

Gestation period	Birth weight			Low birth weight			ZWH			ZWA			ZHA		
	10th percentile	P.E	90th percentile	Best	P.E	Worst	10th percentile	P.E	90th percentile	10th percentile	P.E	90th percentile	10th percentile	P.E	90th percentile
1st Trimester	-0.29	-0.45	-0.39	0.22	0.39	0.24	0.51	0.71	0.55	0.39	0.5	0.33	0.05	0.14	0.06
	(0.32)	(0.34)	(0.3)	(0.27)	(0.27)	(0.3)	(0.79)	(0.84)	(0.78)	(0.63)	(0.68)	(0.65)	(0.52)	(0.55)	(0.54)
2nd Trimester	0.39*	0.35*	0.34*	-0.07	-0.08	-0.005	0.91	1.13*	0.93	0.71	0.98*	0.53	0.044	0.145	0.111
	(0.22)	(0.21)	(0.21)	(0.15)	(0.15)	(0.18)	(0.59)	(0.58)	(0.61)	(0.57)	(0.57)	(0.67)	(0.55)	(0.57)	(0.57)
3rd Trimester	-0.36	-0.27	-0.26	0.07	0.06	0.32	-0.16	-0.01	0.04	-0.37	-0.26	-0.15	-0.58	-0.51	-0.32
	(0.29)	(0.3)	(0.29)	(0.16)	(0.17)	(0.22)	(0.61)	(0.6)	(0.59)	(0.54)	(0.56)	(0.55)	(0.64)	(0.63)	(0.61)
Observations	*1771*	*1764*	*1771*	*1771*	*1764*	*1771*	*2055*	*2052*	*2055*	*2190*	*2186*	*2190*	*2165*	*2159*	*2165*
Clusters	*329*	*329*	*329*	*329*	*329*	*329*	*335*	*335*	*335*	*338*	*338*	*338*	*337*	*337*	*337*
	25th percentile	P.E	75th percentile				25th percentile	P.E	75th percentile	25th percentile	P.E	75th percentile	25th percentile	P.E	75th percentile
1st Trimester	-0.3	-0.45	-0.4				0.53	0.71	0.54	0.4	0.5	0.39	0.11	0.14	0.04
	(0.32)	(0.34)	(0.3)				(0.79)	(0.84)	(0.79)	(0.64)	(0.68)	(0.64)	(0.53)	(0.55)	(0.53)
2nd Trimester	0.36*	0.35*	0.34				0.92	1.13*	0.93	0.69	0.98*	0.73	0.064	0.145	0.101
	(0.21)	(0.21)	(0.21)				(0.59)	(0.58)	(0.61)	(0.58)	(0.57)	(0.58)	(0.55)	(0.57)	(0.56)
3rd Trimester	-0.34	-0.27	-0.28				-0.12	-0.01	-0.02	-0.34	-0.26	-0.28	-0.48	-0.51	-0.384
	(0.29)	(0.3)	(0.29)				(0.6)	(0.6)	(0.59)	(0.54)	(0.56)	(0.53)	(0.62)	(0.63)	(0.61)
Observations	*1771*	*1764*	*1771*				*2055*	*2052*	*2055*	*2190*	*2186*	*2190*	*2165*	*2159*	*2165*
Clusters	*329*	*329*	*329*				*335*	*335*	*335*	*338*	*338*	*338*	*337*	*337*	*337*

Notes: This table presents the results for the bounds test. All the regressions include controls and fixed effects for birth year-month, survey year, district, and district-birth year-specific linear time trend. Controls included are: household head's education and age and a dummy for female head, household size, number of individuals in household of age 0-5, 6-14, 15-24, 25-49, and child's age and gender (dummy for female). The selected sample is children living in rural-coast area and the standard errors are clustered at the district level. Values for simulation were 5.4 mill. for Q1 and Q2, and 4.9 mill. for Q3 corresponding from average destruction due to the impact of at least one hurricanes in the period. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Appendix Table 9. Bound analysis. Using destruction due to two or more hurricanes

Gestation period	Birth weight			Low birth weight			ZWH			ZWA			ZHA		
	10th percentile	P.E	90th percentile	Best	P.E	Worst	10th percentile	P.E	90th percentile	10th percentile	P.E	90th percentile	10th percentile	P.E	90th percentile
1st Trimester	-0.45	-0.73*	-0.57	0.07	0.35	0.24	0.69	1.02	0.67	0.8	0.86	0.74	0.23	0.5	0.29
	(0.38)	(0.44)	(0.37)	(0.29)	(0.34)	(0.32)	(1.24)	(1.42)	(1.25)	(1)	(1.16)	(1)	(1.2)	(1.23)	(1.18)
2nd Trimester	-0.46	-0.7	-0.62	0.29	0.56*	0.67*	-0.4	-0.21	-0.33	0.22	0.25	0.2	1.014	1.089	1.061
	(0.49)	(0.56)	(0.51)	(0.27)	(0.31)	(0.28)	(0.91)	(0.92)	(0.89)	(0.81)	(0.79)	(0.78)	(0.99)	(0.93)	(0.92)
3rd Trimester	-0.22	-0.13	-0.09	0.04	0.11	0.35*	-1.55*	-1.4*	-1.35	-1.61**	-1.88***	-1.49**	-0.55	-0.52	-0.46
	(0.48)	(0.47)	(0.44)	(0.15)	(0.16)	(0.2)	(0.89)	(0.79)	(0.83)	(0.72)	(0.67)	(0.75)	(0.94)	(0.94)	(0.93)
Observations	*1771*	*1764*	*1771*	*1771*	*1764*	*1771*	*2055*	*2052*	*2055*	*2190*	*2186*	*2190*	*2165*	*2159*	*2165*
Clusters	*329*	*329*	*329*	*329*	*329*	*329*	*335*	*335*	*335*	*338*	*338*	*338*	*337*	*337*	*337*
	25th percentile	P.E	75th percentile				25th percentile	P.E	75th percentile	25th percentile	P.E	75th percentile	25th percentile	P.E	75th percentile
1st Trimester	-0.46	-0.73*	-0.56				0.73	1.02	0.66	0.84	0.86	0.78	0.37	0.5	0.23
	(0.38)	(0.44)	(0.37)				(1.24)	(1.42)	(1.24)	(0.99)	(1.16)	(0.98)	(1.19)	(1.23)	(1.16)
2nd Trimester	-0.5	-0.7	-0.56				-0.35	-0.21	-0.37	0.25	0.25	0.19	1.116	1.089	1.018
	(0.49)	(0.56)	(0.51)				(0.9)	(0.92)	(0.9)	(0.8)	(0.79)	(0.77)	(0.96)	(0.93)	(0.91)
3rd Trimester	-0.17	-0.13	-0.11				-1.5*	-1.4*	-1.4*	-1.56**	-1.88***	-1.62**	-0.45	-0.52	-0.49
	(0.46)	(0.47)	(0.45)				(0.87)	(0.79)	(0.84)	(0.71)	(0.67)	(0.73)	(0.94)	(0.94)	(0.92)
Observations	*1771*	*1764*	*1771*				*2055*	*2052*	*2055*	*2190*	*2186*	*2190*	*2165*	*2159*	*2165*
Clusters	*329*	*329*	*329*				*335*	*335*	*335*	*338*	*338*	*338*	*337*	*337*	*337*

Notes: This table presents the results for the bounds test. All the regressions include controls and fixed effects for birth year-month, survey year, district, and district-birth year-specific linear time trend. Controls included are: household head's education and age and a dummy for female head, household size, number of individuals in household of age 0-5, 6-14, 15-24, 25-49, and child's age and gender (dummy for female). The selected sample is children living in rural-coast area and the standard errors are clustered at the district level. Values for simulation were 5.4 mill. for Q1 and Q2, and 4.9 mill. for Q3 corresponding from average destruction due to the impact of at two more hurricanes in the period. Significance at the one, five and ten percent levels is indicated by ***, ** and * respectively.

Appendix 1: Jamaica Labor Force Survey and Jamaica Survey of Living Conditions Design

The Jamaica Labor Force Survey (LFS) is designed as a two-stage stratified random sample. The first stage includes a selection of Primary Sampling Units (PSUs), and the second stage a selection of dwellings. A PSU is an Enumeration District (ED) or a combination of EDs that is selected for a sample, usually containing a minimum of approximately 100 dwellings in the rural areas and a minimum of 150 dwellings for the urban communities. An ED is an independent geographic unit sharing common boundaries with contiguous EDs. After the random selection of PSUs, a listing operation of the dwellings located in each PSU is executed to define the master sample for the LFS. This master sample is revised every three to four years usually implying a new selection of PSUs, listing operation and revised selection of dwellings.

The LFS includes a rotating panel scheme as follows. Once the selected PSUs are listed, 32 dwellings are randomly selected from each PSU. These 32 dwellings are then divided into eight groups or panels of four dwellings each. Dwellings in panels 1 to 4 are interviewed in the first quarter LFS (16 dwellings per PSU each quarter). Dwellings in panels 3 to 6 are interviewed in the second quarter LFS. Dwellings in panels 5 to 8 are interviewed in the third quarter LFS. Dwellings in panels 1, 2, 7 and 8 are interviewed in the fourth quarter LFS. In the first quarter of the following year dwellings in panels 1 to 4 are interviewed again and the yearly cycle is repeated (Table A1). This rotating panel scheme with the same dwellings lasts until the master sample is revised usually every three to four years.

Table A1: LFS Rotating Panel Scheme within each PSU

		Panel							
Year	LFS Quarter	1	2	3	4	5	6	7	8
t	January	▨	▨	▨	▨				
	April			▨	▨	▨	▨		
	July					▨	▨	▨	▨
	October	▨	▨					▨	▨
t+1	January	▨	▨	▨	▨				
	April			▨	▨	▨	▨		
	July					▨	▨	▨	▨
	October	▨	▨					▨	▨

Jamaica is administratively divided into 14 parishes. Each quarterly LFS is representative at the parish and the national level. The Survey of Living Conditions (SLC) usually covers a nationally representative subsample of the April LFS (covering approximately a third of the EDs sampled in the LFS). However, periodically every four or five years, the SLC covers the entire April LFS sample. This exercise is periodically conducted with the objective of producing consumption and poverty aggregates not only at the national level but also at the parish level with acceptable standard errors. Table A2 shows the number of EDs surveyed in the April LFS and SLC corresponding to the yearly periods used in our analyses. Within our study period, years 1996, 2002, 2008, and 2012 included large SLC samples covering the entirety of EDs surveyed in the April LFS.

Table A2: Surveyed EDs in the April LFS and SLC

Year	April LFS EDs	SLC EDs	% SLC Sample	No.Children 0 -5 years old in survey (comp. sample)	No.Children 0 -5 years old in survey (Coast-rural)
1993	n.a.	156	n.a.	838	81
1996	155	155	1.00	783	105
1997	n.a.	160	n.a.	771	166
1998	n.a.	478	n.a.	2,758	603
1999	n.a.	160	n.a.	651	127
2000	n.a.	161	n.a.	617	109
2002	522	522	1.00	2,271	465
2004	505	169	0.33	647	124
2006	507	170	0.34	527	79
2007	508	168	0.33	583	74
2008	612	612	1.00	1,696	275
2010	507	169	0.33	418	61
2012	508	508	1.00	1,551	300