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Weathering Storms

Understanding the Impact of Natural Disasters on the Poor in Central America

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Abstract

In the past decades, natural disasters have caused substantial human and economic losses in Central America, with strong adverse impacts on gross domestic product per capita, income, and poverty reduction. This study provides a regional perspective on the impact of hurricane windstorms on socioeconomic measures in the short term. Apart from modeling the socioeconomic impact at the macro and micro levels, the study incorporates and juxtaposes data from a hurricane windstorm model categorizing three hurricane damage indexes, which lends a higher level of detail, nuance, and therefore accuracy and comprehensiveness to the study. One standard deviation in the intensity of a hurricane windstorm leads to a decrease in growth of total per capita gross domestic product of between 0.9 and 1.6 percent, and a decrease in total income and labor income by 3 percent, which in turn increases moderate and extreme poverty by 1.5 percentage points. These results demonstrate the causal relationship between hurricane windstorm impacts and poverty in Central America, producing regional evidence that could improve targeting of disaster risk management policies toward those most impacted and thus whose needs are greatest.

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Weathering Storms: Understanding the Impact of Natural Disasters on the Poor in Central America[1]

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1. INTRODUCTION

Due to its geographical location and its geological and hydro-meteorological characteristics, Central America is remarkably prone to disasters from adverse natural events. Five of its six countries are ranked in the top 15 countries with the highest risk of mortality and economic loss from three or more natural hazards (World Bank, 2010).

With the highest poverty rates in Latin America, Central America's population is particularly vulnerable to disasters from adverse natural events. About 42 percent of the region's population (around 41 million people) is poor or extremely poor (Krozer, 2010). As of 2013, Guatemala, Honduras, and El Salvador have the highest poverty rates in Latin America with 62.4, 59.4 and 31.8 percent of their populations living on less than US$ 4 per day respectively (World Bank, 2015). Disasters from adverse natural events exacerbate Central America's economic vulnerability, accounting for substantial human and economic losses.

In the last decade alone, between 2005 and 2014, the region had a nominal combined cumulative loss of around US$ 5.8 billion, with more than 3,410 deaths and hundreds of thousands of people displaced.[4] Hydro-meteorological events are not only the most common of Central America's natural disasters, but are also the events with the widest range and impact in the region. In 1998, Hurricane Mitch caused about 14,600 deaths, directly affected around 6.7 million people, and caused more than US$ 8.5 billion in damages in Nicaragua, Honduras, Guatemala, and El Salvador. More recently, in October 2011, Tropical Depression 12-E hit the coasts of El Salvador and Guatemala, causing damage in most of the countries in the region, which totaled almost US$1 billion (CEPAL, 2011).

Recent and growing evidence suggest that disasters have a negative impact on short-term overall economic growth, increasing poverty and lowering human development indicators (Anttila-Hughes & Hsiang, 2013; Lucchetti, 2011; Rodriguez-Oreggia et al., 2012). Other studies have found that disasters may also reduce household consumption substantially, causing significant welfare losses (Dercon, 2005; Thomas et al., 2010). Although there is less available evidence of the long-term impact of disasters, Hsiang & Jina (2014) present results at the global level which indicate that persistent negative effects of cyclone strikes could last for as long as 20 years after the event. However, by contrast, Raddatz (2009) only found highly concentrated effects of the impacts of droughts and windstorms on national income on the year of the event.[5]

In Central America, evidence shows that major disasters affect households negatively, especially in the form of disinvestments in human capital. Analyzing the impact of Hurricane Mitch in Nicaragua, Baez and Santos (2007) find that the probability of child undernourishment in regions hit by Hurricane Mitch increased by 8.7 percent, while child labor force participation increased by 5.6 percent. Carter et al. (2007) looked at the impact of Hurricane Mitch in Honduran households, and found that lowest-income groups were impacted more severely, and for longer periods. In Guatemala, Bustelo (2011) analyzed the impact of Storm Stan and found that the probability of child labor increased by 7.3 percent in departments hit by the storm. Also in Guatemala, Baez et al. (2015) looked at the consequences of Tropical Storm Agatha (2010) on household welfare, finding that consumption per capita fell by 12.6 percent and poverty increased 5.5 percentage points (an 18 percent increase).

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[4] Calculation of authors based on information from EM-DAT: The international Disasters Database.

[5] Dell, Jones and Olken (2014) provide an excellent review on the new climate-economy literature and summarize results on different socioeconomic outcomes (e.g., health, conflict, economic growth, among others).

These studies show the impact of major events in specific socioeconomic conditions. As there is an absence of regional studies focused at both macro and household levels, the contribution of this study is to provide a regional perspective to the negative impact of hurricane windstorm on a particular set of social and economic outcomes. This is relevant not only because a systematic regional perspective is currently absent in the existing literature, but also because the region shares many characteristics and a common approach to disaster and climate risk management.

The second section of this study investigates the interconnection between hazard and damage which determine the impacts found by empirical studies. In this section we discuss how windstorm hazard data are translated into damage indexes, and present three different ways of computing hurricane damage indexes. To characterize hurricane windstorm we draw on a model developed in the WBG Latin-American and the Caribbean Disaster Risk Management (DRM) team by Pita et al. (2015) which employs a fully probabilistic hurricane windstorm model calibrated and adjusted for Central America. This model has been used to reproduce historical hurricanes windstorm characteristics with higher temporal and spatial resolution. This model allows a richer and more accurate characterization of the hurricane windstorm hazard than heretofore seen in the literature, improving the different damage indexes used and enabling better understanding of the implicit biases in the model.

Sections 3 and 4 of the study turn to the data, methodology, and results of the analysis at macro and micro (household analysis) levels, focusing on the strong negative impacts of major hurricanes in the short term on per capita GDP (gross domestic product) growth, income, and poverty. One standard deviation in the intensity of hurricane windstorm leads to a decrease in total per capita GDP growth of between 0.9 percent and 1.6 percent, and a decrease in total income and labor income by 3 percent; which in turn increases moderate and extreme poverty by 1.5 percentage points. These socioeconomic indicators are further informed by 3 indexes derived from hurricane damage modeling. Studying both the macro (per capita GDP growth) and the micro (household poverty and income among the variables) levels encompasses a more comprehensive level of analysis of impacts of hurricane windstorms, resulting in a more detailed and nuanced understanding of the negative economic implications of such events.

Finally, the concluding section draws all these angles together to provide a more comprehensive analysis, provides recommendations, and throws up research questions for the future.

2. FROM WINDSTORM HAZARD TO DAMAGE

Recent studies have focused on improving the modeling of the natural hazard in order to more explicitly address the impact of adverse natural events on socioeconomic indicators. For example, Hsiang and Jina (2014) and Strobl (2012) evaluate the hurricane windstorm hazard data using global hurricane models to generate gridded data sets with different levels of resolution (Hsiang and Jina at the global level and Strobl for the Caribbean basin). One of the main innovations of this paper is to use a fully probabilistic hurricane windstorm model developed by Pita el al. (2015) which has been validated and calibrated for the Central America region to generate hazard information with the temporal and spatial resolution needed for this study. The windstorm hazard data are used to calculate the damage indexes which are used as input in both the macro and micro models. As a result we substantially improve the understanding of how hurricane windstorm hazards could affect socioeconomic outcomes.

2.1. Modeling the Windstorm Hazard

Being complex, the dynamic atmospheric environment of windstorms is often oversimplified. This study uses an accurate and comprehensive model that generates high-resolution surface-level sustained wind speed data of historic hurricanes and tropical storms in Central America. This novel windstorm hazard model for Central America has been developed by the WBG Latin-American and the Caribbean Disaster Risk Management (DRM) team as part of the development of Country Disaster Risk Profiles.[6]

The windstorm hazard model, described in more detail in Pita et al. (2015), is a wind field model to estimate surface gust wind speeds and a mechanism to generate synthetic events and trajectories. One of the key outputs of the model is the generation of maximum wind speeds along the trajectory of the hurricane. Wind speeds refer to the tangential wind component of the hurricane and are directly related to the intensity of the event. This model has been tested, calibrated, and validated with observed activity in the East Pacific and North Atlantic basins for the Central America region. The model's forecasts conform acceptably well with the observed wind speeds, which guarantees the accuracy of the data used.

The wind speed model used is grounded in the asymmetric Holland equation, which is characterized by its simplicity (i.e. the number of model parameters) and its accuracy (i.e. the coincidence of model's predictions with observed measurements).

The model reproduces the geographical distribution of the tangential gradient wind speeds, *Vg,* or wind gusts at a height of 10 meters over a 1km^2 grid, using the Holland model as represented in Equation 1. The wind speed is measured at this height because it is here that wind speeds do the most damage.

$$V_g = W_0 + \sqrt{W_0^2 + \left(B.\frac{\Delta p}{\rho}\right).\left(\frac{RMW}{r}\right)^B .exp\left[-\left(\frac{RMW}{r}\right)^B\right]} \qquad (1)$$

Where:

$W_0 = \frac{V_T \sin(\varphi) - f.r}{2}$

B is Holland's shape parameter;

Δp is the deficit of central and outer peripheral pressure (in Pascals);

ρ is the air density at the gradient height (kg/m3);

RMW is the radius of maximum winds (in meters);

r is the radius of any location to the center of the storm (in meters);

V_T is the hurricane translation speed (in meters per second);

f is the Coriolis parameter (in 1/seconds);

φ is the angle between the North and the storm heading.

Holland's shape parameter (B) incorporates some characteristics of the terrain. Roughness, for example, may affect angular momentum due to surface friction. These variables have been calibrated for the Central American region using different sources: terrain roughness from the Global Land Cover Dataset 2000, topography data from the Shuttle Radar Topography Mission data base, speed-up occurring in escarpments and ridges using the methodology proposed by the American Society of Civil Engineers in 1994, and wind gusts factors using Vickery and Skerlj's (2005) estimation method.

To assess the model's accuracy and applicability, the estimates were evaluated against the tracks and wind fields of historical events. Predicted results by the model were compared to the values reported by the United States' National Oceanic and Atmospheric Administration (NOAA) aircraft for Hurricanes Mitch

[6] This research has been funded by the World Bank through a Global Facility for Disaster Reduction and Recovery (GFDRR) grant (TF014499) from the Government of Australia (AusAid) under the CAPRA Probabilistic Risk Assessment program (P144982).

(1998) and Stan (2005) to assess the accuracy of simulated data on wind speed. To further evaluate the accuracy of the results, model estimations were also compared with simultaneous in-situ measurements collected during the passage of Hurricanes Jeanne and Frances in 2004 across Florida (Pita el al., 2015). These robustness checks provide important information about the accuracy of information generated by the model.

The use of this wind speed model is a key innovation in this study since it represents a completely exogenous input in the estimation of hurricanes' potential destructive power at each geographical location, which is completely calibrated and validated for the Central America region. Strobl (2012) and Hsiang and Jina (2014) focus their papers on maximum wind speed using a more simplistic hurricane model not necessarily calibrated for our region of interest.

2.2. Hurricane Damage Indexes

Having precise windstorm hazard data is the first step in the study's characterization of hurricane impact. What makes hurricanes destructive, and hence economically disruptive, is the strong wind speed coming in contact with exposed assets and buildings. In a storm, strong winds run into stationary objects (e.g., trees, buildings, cars, etc.). Some of these elements can safely absorb the energy carried in the moving air, while others cannot. To illustrate this connection, consider two hurricanes of the same magnitude, with the only difference being that one of them strikes a densely populated area, while the other one touches upon an isolated region. These two virtually identical hurricanes will have extremely different and opposite economic impacts. The consideration of exposure of assets and population is a key factor for the estimation of damages. To keep the exogeneity of the hurricane's damages indexes represents a challenge, as it is difficult to link each economic unit with the level of wind by which it has been hit.[7]

In this study we consider three approaches based on 3 different indexes, as outlined in the recent literature. The first one is simply using the maximum sustained wind speed (MSWS) as generated by the Pita et al. model, representing a fully exogenous measure of hurricane intensity. This variable being fully exogenous, comprises potentially high levels of measurement error.

The second approach, proposed by Hsiang and Jina (2014), is the Wind Exposure Index (WEI) describing a spatially-weighted index by area exposed to hurricane wind speed within a sub-national unit (see Equation 2). This index aims to recover the average effect of hurricane exposure on an average grid. As Hsiang and Jina (2014) suggest, intuitively the WEI index represents the exposure all units of land would have if the measure of a storm is "spread out" evenly across all locations in a country. If exposed area is correlated with socioeconomic damages, but the overall intensity of a storm is not correlated with populated or economically active regions or countries, measurement error is reduced.

$$WEI_{ijy} = \frac{\sum_{n=1}^{N} V_n * A_n}{\sum_{n=1}^{N} A_n} \qquad (2)$$

[7] Another aspect that needs to be addressed in the characterization of hurricanes is the temporal and spatial mismatch between socioeconomic data and wind speed data. Socioeconomic data are often collected, calculated or released at an aggregate level by country or region on a yearly basis. Meanwhile, wind speed data are available at a finer resolution ($1km^2$) for each point in time. In the case of the GDP analysis (section 3), indexes are aggregated at the country level, while in the case of the household analysis (section 4), indexes are aggregated at the sub-national level (regions).

Where:
j: is the subnational region, y is the year and i denotes each event;
n: is the unit (grid) of observation of wind sped;
N: is the total number of grids per region (or sub-national unit);
V_n: is the maximum sustained wind speed;
A_n: is the area of the grid.

The third approach is the Index of Hurricane Destruction (IHD), proposed by Strobl (2012). This index uses the distribution of population as a proxy for economic activity, weighting the MSWS of a given cell by the percentage of the population within the cell (see equation 3). This index further reduces the measurement error, albeit at the cost of potential endogeneity issues because population could make the decision of locate themselves strategically on low-hazard areas.[8]

$$IHD_{ijy} = \sum_{n=1}^{N} MSWS_n^{\lambda} * W_n \qquad (3)$$

Where:
$\mathrm{W_n}$: is the percentage share of the country's population;
λ: is the damage factor (equal to 3.8);[9]
n: is the unit (grid) of observation of wind speed;
N: is the total number of grids per region.

2.3. Intensity Threshold

Given the non-linearity on the relationship between MSWS and the damage on the ground,[10] we evaluate the impact of hurricanes measured by the Saffir-Simpson (SS) scale.[11] The SS scale classifies events into five categories according to the sustained wind speed measurement, with one being of the lowest and five the highest wind speed. The wind speed is directly correlated with the intensity of the hurricane. The scales are as follow: 1 for hurricanes between 119 and 153 km/h, 2 for hurricanes between 154 and 177 km/h, 3 for hurricanes between 178 and 209 km/h, 4 for hurricanes between 210 and 249 km/h, and 5 for hurricanes above 250 km/h.[12]

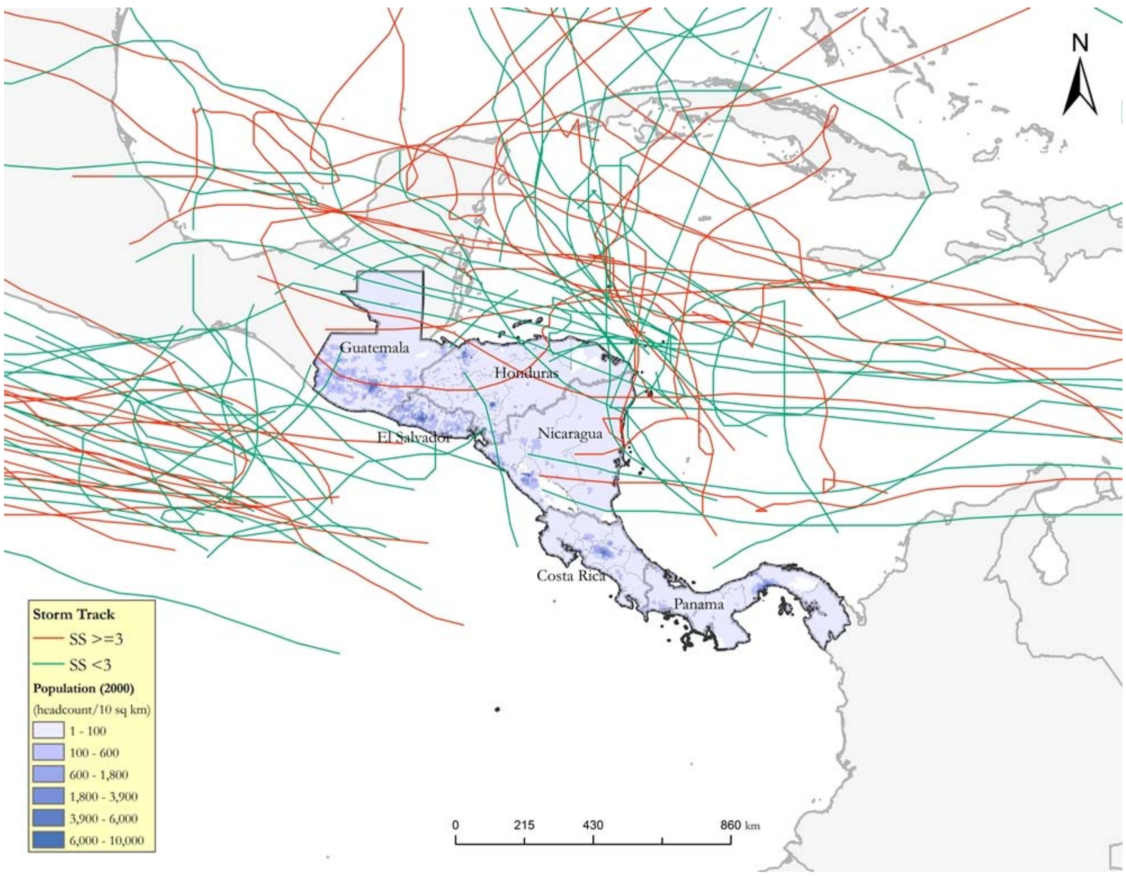
As Strobl (2012) suggests, it is generally agreed that considerable damages due to windstorm only occur once a hurricane reaches a strength of 3, which is intrinsically how the scale has been created. In the case of Central America, however, it is unclear whether this relationship holds given the high levels of poverty and the fragile residence features in the region.[13] Therefore, this is an empirical question that we address

[8] We use the GHSL – Global Human Settlement Layer Population dataset for available years (1975, 1990, 2000, and 2015).
[9] Strobl (2012) suggests that this parameter relates local wind speed to the local level of damages.
[10] Each additional unit of wind speed does not cause a constant level of damage.
[11] The National Hurricane Center provides further explanation and a conceptual animation of the SS categories: http://www.nhc.noaa.gov/aboutsshws.php.
[12] Related categories are tropical storm (63 – 118 km/h) and tropical depression (≤ 62 km/h).
[13] For example, according to SEDLAC, the share of dwellings of low-quality materials in Central America could be high as in Guatemala (46 percent), El Salvador (31 percent), Nicaragua (15 percent), and Honduras (14 percent).

here. We considered two group of analysis: (a) events with SS equal or higher than 1, (b) events with SS equal or higher than 3.

As an example, Figure 1 shows all the historical hurricanes since 1983 single out by SS scale and the distribution of population based on data from 2000. This graph depicts three key features. First, most of the hurricanes are considered below SS scale 3 (out of the 92, 35 are considered of SS scale 3 or greater). Secondly, we show that Honduras, Guatemala and Nicaragua are the most impacted countries in the region, whereas Costa Rica and Panama have not been hit by any major hurricane in the last 30 years. Thirdly, population is highly concentrated in the western area of Central America where there are a fewer storm occurrences. The proposed indexes –especially the population weighted index, IHD– incorporate that dynamic when assessing the related economic damages.

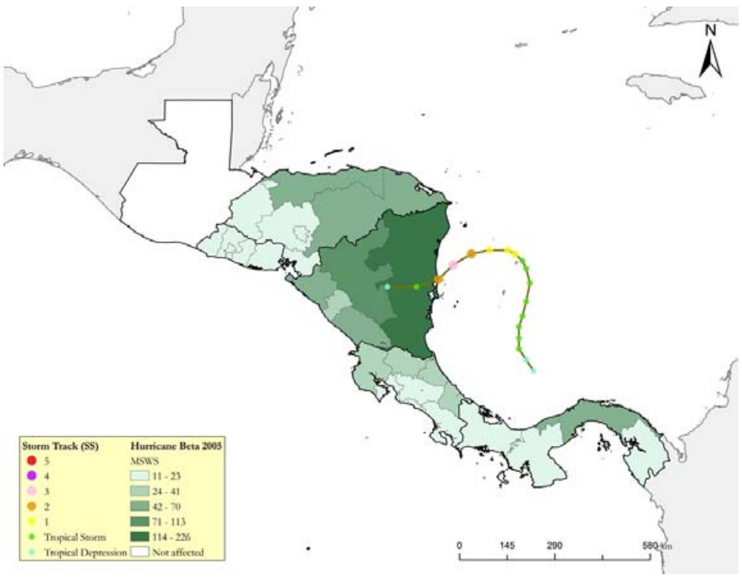
Figure 1
Central America's Strom Tracks by Intensity



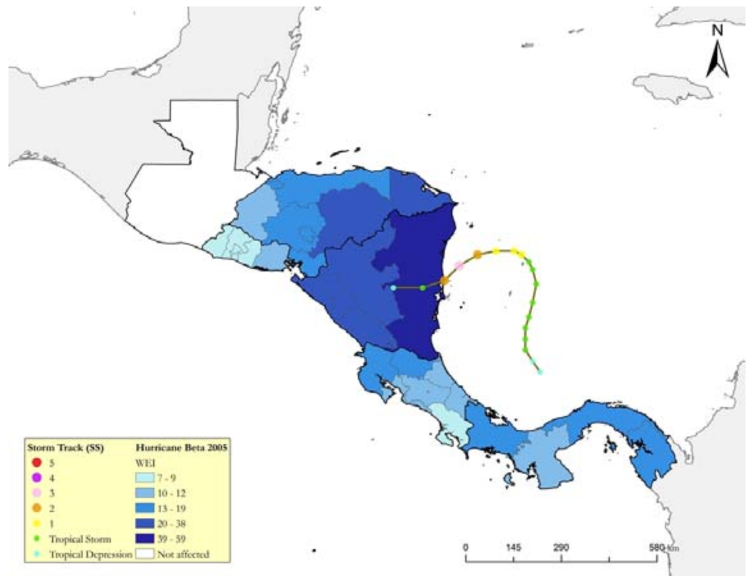
The correlation between the three indexes is considerably high. Figure 2 depicts the three indexes aggregated at the SEDLAC regional level[14] for Hurricane Beta (2005). Hurricane Beta was considered of category 3 before landfall and it substantially affected Nicaragua. In land, depending in the country, Beta was considered a hurricane category 2 and a tropical storm. The three embedded graphs show clearly that the three indexes share more similarities than differences. Among the six countries, Nicaragua and Honduras were the most affected and similar conclusion is derived from each index (besides its unit of measure).

Figure 2
Hurricane Damage Indexes for Hurricane Beta (2005)

Maximum Sustained Wind Speed (MSWS)

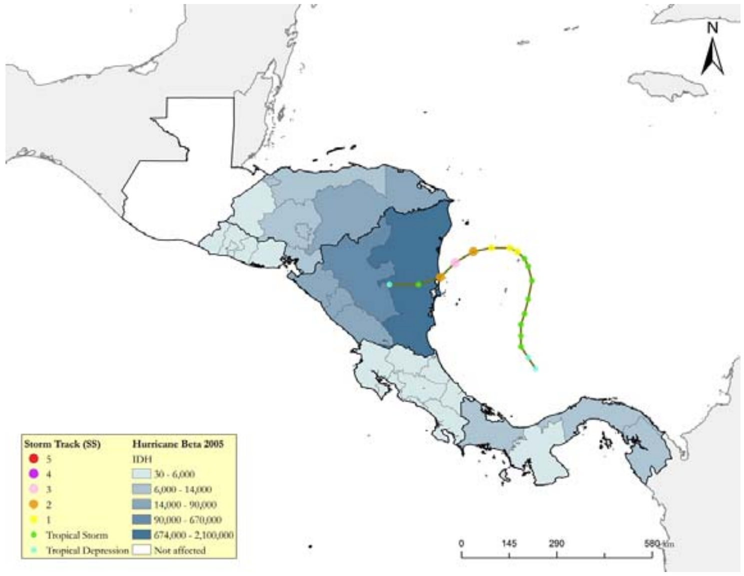


Wind Exposure Index (WEI)



Index of Hurricane Destruction (IHD)

[14] SEDALAC: Socio-Economic Database for Latin America and the Caribbean (Universidad Nacional de La Plata/World Bank). Please refer to section 4 for further details on the regions considered at the household level analysis.



Note: Countries are divided in SEDLAC regions. SEDLAC is the World Bank Socio-Economic Database for Latin America and the Caribbean.

3. WINDSTORM IMPACT AT THE MACRO LEVEL

This section presents the data, methodology, and results of the analysis at a macro level, focusing on how hurricane windstorm impacts per capita GDP growth in Central American countries over a period of almost 30 years (1983 – 2010). The unit of analysis is the country and our empirical strategy exploit countries' variation over time to identify the causal effect of storms on GDP.

3.1. Data

The main database used in this analysis is from version 7.1 of the Penn World Tables (PWT), published on November 2012.[15] Results are comparable as the PWT database was also used by Hsiang and Jina (2014) and Strobl (2012). Compared to previous PWT databases, version 7.1 basically changes the reference year from 2005 to 2010, introduces improvements in regional price comparisons, and increases the number of countries covered.[16]

The period of analysis is roughly 30 years (1983-2010); a period which matches the availability of wind speed data. The key dependent variable is GDP per capita. Other control variables include: population, openness (sum of imports and exports as a share of total GDP), and investment (defined both as capital formation from national accounts and also as a share of total GDP). These covariates are included in the

[15] Although other data sources like the World Development Indicators and the IMF's World Economic Outlook Data were considered, for comparability with Strobl (2010) and Hsiang & Jina (2014) as well as other papers relevant to this study, the results presented in this study are based on Penn World Tables data.

[16] Even though at the time of the analysis a newer version of the tables had been released, significant changes in the variables from the previous editions reduced comparability with results from Hsiang and Jina (2014) and Strobl (2012), hence we decided to work with version 7.1.

Strobl (2012) analysis. All variables in monetary terms are measured in current Purchasing Power Parity (PPP), international dollars allowing for comparability between countries.

The average GDP per capita for the region is US$ 4,478, with an average annual growth rate of 3.6 percent in this period. This number masks important differences between countries. In the study period, Costa Rica and Panama experienced higher growth rates than the rest of the Central American countries. For example, in 2010, Costa Rica's and Panama's GDP per capita was twice the one of El Salvador's and Guatemala's, and thrice that of Nicaragua's and Honduras'. While Panama grew at an average rate of 5.3 percent per year, Nicaragua (which suffered a political revolution in the studied period) grew by only 1.5 percent.

Table 1 presents descriptive statistics by decade of the variables used in the analysis. Central American countries have experienced trade liberalization in recent years, resulting in trade openness in the region growing from 0.47 to 0.76 between 1990 and 2000. There is, however, important variation between countries and across this time period: for example, Panama, the country with the highest openness index, trades 145 percent of its GDP, while El Salvador trades only 59 percent of its GDP on average. Also, in this period, the population in the region grew at an average rate of 2.1 percent, but this increase was far higher in urban areas, which has led to a concentration of the population in big cities. The size of the countries' population is also variable, with Guatemala being the largest with 10 million inhabitants, while Panama, with 2.7 million inhabitants, has the smallest population.

Table 1
Descriptive Statistics: Macroeconomic Variables

Decade	Statistics	GDP PC	GDP PC Growth	Investment	Openness	Population
1983-1990	Mean	2,947	2.3%	16.3%	65.7%	4,241
	SD*	1,006	5.9%	5.3%	31.4%	1,955
	Min	1,532	-25.9%	4.3%	17.0%	2,081
	Max	5,470	10.6%	28.1%	146.8%	8,966
1991-2000	Mean	4,091	3.8%	22.4%	89.6%	5,311
	SD*	1,836	3.7%	6.0%	39.9%	2,450
	Min	1,463	-6.1%	13.6%	41.5%	2,441
	Max	8,471	13.4%	40.4%	178.6%	11,085
2001-2010	Mean	6,090	4.3%	22.9%	97.7%	6,385
	SD*	3,074	3.1%	5.1%	29.5%	3,015
	Min	1,922	-3.9%	13.6%	57.2%	2,952
	Max	12,983	11.9%	33.2%	161.2%	13,550
Total	Mean	4,478	3.6%	20.8%	85.7%	5,389
	SD*	2,545	4.3%	6.2%	36.4%	2,673
	Min	1,463	-25.9%	4.3%	17.0%	2,081
	Max	12,983	13.4%	40.4%	178.6%	13,550

*Standard Deviation

3.2. The Model

The data are a balanced panel spanning 28 years for the 6 countries in Central America (Guatemala, Honduras, Costa Rica, Panama, Nicaragua, and El Salvador). As discussed in the previous section, wind speed data was aggregated by year. When more than one event occurred in a calendar year in the same country, only the strongest event was taken into account. To evaluate the existence of other relationships between multiple hurricanes in a year and per capita GDP growth, we included controls for the number of hurricanes per year with no substantial change in the results.[17]

During the 30 years of the study, only four hurricanes reached SS scale equal to or greater than 3,[18] while 19 events reached SS scale equal to or greater than 1. It is important to highlight that in this period, Panama and Costa Rica did not suffer any major events (i.e., events with SS ≥ 1). Nicaragua accounted for nearly half of the events (9 events in total) followed by Honduras (5 events in total). Storms under category SS 1 represented 63 percent of events (12 in total), while category SS 2 and SS 3 accounted equally for nearly 33 percent of total events.

Our empirical strategy exploit the natural random variation in the formation, path and intensity of hurricanes and tropical storms as a source of exogenous within-country variation in disaster exposure to identify the causal effect of hurricanes in per capita GDP. It follows an ordinary least squares (OLS) models with fixed effects by year and country. Hence our identification strategy exploits the variation over time within countries following equation 4.

$$y_{it} = \alpha + \beta H_{it} + \delta X_{it} + \theta t + \gamma_t + \mu_i + + \varepsilon_{it} \qquad (4)$$

Where:

y_{it} is per capita GDP growth for country *i* in year *t;*
H_{it} is the hurricane damage index for major events for country *i* in year *t* (SS ≥ 1 or 3);
X_{it} is a matrix of control variables;
γ_t are year fixed effects;
μ_i are country fixed effects;
θ is time trend.

For each country, the dependent variable is per capita GPD growth. As we discussed in the previous section, we adopted three different measures of the intensity of the damage (H_{it}): MSWS, IHD and WEI. MSWS corresponds to the unweighted wind speed aggregated at the country level per year, IHD relates to the population-weighted wind speed, while WEI relates to the area-weighted wind speed. Each index has its strengths and weaknesses highlighting the trade-off between exogeneity and measurement error.

The control variables (X_{it}) mirror those in Strobl (2012) and include: investment as a percent of GDP, population growth, openness (the sum of exports and imports as a percentage of GDP), and the log of GDP per capita. All these variables are lagged one period to capture the contemporary economic impact of hurricanes in the region. Additionally, a regional time trend (θ) was included to account for common factors to all countries.

[17] Results available upon request.
[18] Nicaragua: Joan (1998), Cesar (1996), Felix (2007). Honduras: Mitch (1998).

3.3. Results

Table 2 and Table 3 present the main results for this section for events. Table 2 shows results for events with SS equal or higher than 1, while Table 3 for events with SS equal or higher than 3. Results are standardized in order to make all the indexes comparable.[19] Column (1) shows results from equation (4) estimated using OLS. These results have potential issues of serial and spatial autocorrelation. Spatial autocorrelation is a concern given that countries are closely located. Serial autocorrelation is a lesser concern since our study period covers approximately 30 years and bias decreases inversely to time. Therefore, column (2) shows results correcting for serial and spatial autocorrelation in line with Hsiang (2010) and Conley (2008). Column (3) estimates the model using panel data and the control variables. Given that we model it dynamically (with the lagged dependent variable as one of the regressors), it potentially have a systematic bias in our coefficient of interest. Therefore, column (4) shows the panel data results correcting for dynamic models in line with Strobl (2012) and Bruno (2005). Column (2) and Column (4) reports the most credible specifications.

Results across all specifications provide similar results and negative as expected (see Table 2).[20] The magnitude of the effects are economically significant. An increase of one standard deviation in the intensity of a hurricane leads to a decrease in total per capita GDP growth of between -0.9 (for MSWS) and -1.6 percentage points (for IHD). It is important to highlight that the variation is explained by the different magnitude of a standard deviation according to the different indexes. For example, in the case of the IHD, a standard deviation is equivalent to a hurricane with a sustained wind speed of 74 mph (SS Scale 1) hitting an area with 2.3 percent of the population, or one with a sustained wind speed of 111 mph (SS Scale 3) in an area with 0.5 percent of the population. For WEI, a standard deviation is comparable to a hurricane affecting 10.6 percent of the country with a sustained wind speed of 74 mph, or one affecting 7.1 percent of the country's territory with a sustained wind speed of 111 mph. To illustrate this, consider Hurricane Mitch which hit Honduras in 1998 with a MSWS of 130.6 mph. [21] Given these parameters, due to the hurricane, the model predicts a decrease in per capita GDP growth of 1.1, 3.1, and 1.9 percentage points for MSWS, IHD, and WEI, respectively.

[19] For example, the IHD index (population-weighted wind speed) powers wind speed to the 3.8, hence unstandardized coefficients are simply smaller than the MSWS and WEI indexes.

[20] Column (1), without controlling for serial and spatial correlation, only shows significant results for IHD but not for the other two indices (MSWS and WEI). When correcting, Column (2) results consistent negative and significant estimates.

[21] Its WEI was 30.41 and its IDH was 699,548.

Table 2
Impact of Major Hurricanes on GDP per capita (SS ≥ 1)

	(1)	(2)	(3)	(4)
	Linear Regression	Linear Regression correcting for Serial & Spatial Autocorrelation	Panel Data with Controls[1/]	Panel Data correcting for Dynamic Models
MSWS	-0.00274	-0.00861*	-0.00839**	-0.00894**
Standard Error	(0.00434)	(0.00469)	(0.00349)	(0.00399)
R-squared	0.314	0.415	0.076	n.a.
IHD	-0.0126*	-0.0148**	-0.0148***	-0.0160***
Standard Error	(0.00540)	(0.00642)	(0.00320)	(0.00375)
R-squared	0.365	0.458	0.157	n.a.
WEI	-0.00498	-0.00994**	-0.00983***	-0.0105***
Standard Error	(0.00569)	(0.00447)	(0.00330)	(0.00394)
R-squared	0.319	0.423	0.093	n.a.

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

[1/] Investment, population growth, openness, log of GDP per capita. All for t-1.

Table 3 shows the results for events with a SS scale equal or greater than 3. As expected, effects are similar but with higher coefficients as evidence of non-linear impacts: stronger hurricanes result in devastating damages. We cannot investigate further since the number of events for storms with SS ≥ 3 are limited (only four events).[22] Other controls considered include the number of events per year, the SS scale, and the inverse of the translation velocity; however, none of these proved significant.

[22] Due to this reason and the lack of power, we hypothesize that results for column (2) in Table 3 are not significant (MSWS and WEI).

Table 3
Impact of Hurricanes on GDP per capita (SS ≥ 3)

	(1)	(2)	(3)	(4)
	Linear Regression	Linear Regression correcting for Serial & Spatial Autocorrelation	Panel Data with Controls[1/]	Panel Data correcting for Dynamic Models
MSWS	-0.0115***	-0.0115	-0.0113***	-0.0123***
Standard Error	(0.00195)	(0.00855)	(0.00324)	(0.00330)
R-squared	0.367	0.434	0.111	n.a.
IHD	-0.0151***	-0.0167**	-0.0169***	-0.0186***
Standard Error	(0.00251)	(0.00840)	(0.00314)	(0.00328)
R-squared	0.405	0.476	0.191	n.a.
WEI	-0.0127***	-0.0135	-0.0134***	-0.0145***
Standard Error	(0.00211)	(0.00914)	(0.00319)	(0.00329)
R-squared	0.379	0.449	0.139	n.a.

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

[1/] Investment, population growth, openness, log of GDP per capita. All for t-1.

We can conclude that the impact of hurricanes in Central America decreases per capita GDP growth in a consistent and statistically significant way. With reference to IHD, an increase in a standard deviation reduces per capita GDP growth by 1.60 percent points, which represents half the average yearly growth of the region. The economic disruption of a shock like this is immense.

4. WINDSTORM IMPACT AT THE HOUSEHOLD LEVEL

One shortcoming of only looking at the impact of hurricanes on GDP is that, as a measure of economic performance and social progress, GDP fails to capture much of what we want to know about human well-being. Although GDP is a good starting point to interpreting the impact of adverse natural events, it is also important to understand its limitations in our context. A disaster could actually boost GDP because of the reconstruction efforts and measures taken by governments. Since GDP is meant to measure market activities –and by definition, self-sustaining agriculture is not in the market– a reading of GDP could undercount or underestimate the impact of a disaster on poor rural populations. It is therefore necessary to consider other welfare measures in order to have a more accurate picture of the impact of hurricanes in the region. In an effort to delve deeper into the effect of hurricanes on the well-being of the population in Central America, this section evaluates hurricanes' impact on income and poverty, as per the World Bank's definition. Even though data are limited, especially for the countries hit most by storms (e.g. Nicaragua and Guatemala), we shed light on the potential impacts for Central America.

4.1. Data

The main databases used in this section are the household surveys. Given constant improvements and changes to the surveys (e.g., changes in questions, sample, and sampling methods, etc.), and lack of comparability across countries, we use the harmonized household surveys developed by the World Bank, named SEDLAC (the Socio-Economic Database for Latin America and the Caribbean). SEDLAC database has harmonized socioeconomic household survey information for 24 countries in Latin America, from 1990 onwards.

In the case of Central America, SEDLAC provides information from 2000 particularly on employment, income, and expenditure. However, surveys are not available or comparable in all years. Since 2000, the available and comparable surveys are as follows: Honduras (2001 – 2013), El Salvador (2004 – 2012), Guatemala (2000, 2006, and 2011), Costa Rica (2001 – 2013), Nicaragua (2005 and 2009), and Panama (2008 – 2013).[23] This data limitation shapes the empirical approach adopted in section 4.2.

Our unit of analysis is a sub-national region. SEDLAC makes available information that is representative at a sub-national level based on the sampling design of each country. Based on this criteria, and prioritizing the comparability over time (i.e., the lowest sub-national level that is covered in all available years), we selected 27 sub-national regions for the six countries in Central America. The average number of (sub-national) regions is 5 per country.

There are four main dependent variables at the household level: per capita labor income, per capita total income, poverty (less than US$ 4 per day) and extreme poverty (less than US$ 2.5 per day). Descriptive statistics are shown in Table 4. Guatemala, Honduras and Nicaragua are the poorest countries in the region with more than 50 percent population living under poverty on average during the last decade. Poverty and extreme poverty has been substantially reduced in Panama, Costa Rica, El Salvador, and Nicaragua. El Salvador shows the strongest extreme poverty reduction from 22 percent in 2004, down to 14.7 percent in 2012. However, in the case of Guatemala and Honduras, poverty has increased marginally. Total income and labor income follows the same pattern as poverty, increasing in Panama and Costa Rica, but decreasing in Honduras and Guatemala.

[23] For further details, please refer to the World Bank's Equity Lab website: http://globalpractices.worldbank.org/teamsites/Poverty/LACDataLab/Pages/TeamHome.aspx

Table 4
Descriptive Statistics: Poverty and Socio-economic Variables

	Panama (2008-2013)	Costa Rica (2001-2013)	El Salvador (2004-2012)	Nicaragua (2005, 2009)	Guatemala (2000, 2006, 2011)	Honduras (2001 - 2013)
Poverty below USD4 (Headcount ratio)						
Average	23.0%	19.4%	40.1%	55.7%	56.8%	58.4%
Min	20.4%	12.2%	34.8%	52.2%	52.6%	50.0%
Max	26.2%	26.7%	46.8%	59.2%	62.4%	64.4%
Poverty below USD2.5 (Headcount ratio)						
Average	12.2%	8.8%	20.8%	33.3%	35.9%	40.4%
Min	9.9%	4.6%	14.7%	29.3%	33.4%	31.3%
Max	14.5%	13.8%	28.6%	37.2%	40.5%	48.0%
Average Total per-capita income						
Average	397.64	399.52	218.97	164.32	182.42	174.06
Min	364.68	321.43	197.18	160.98	156.76	148.56
Max	438.43	506.37	234.52	167.66	198.03	201.56
Average Labor per-capita Income						
Average	275.17	308.50	166.71	128.15	143.79	134.97
Min	246.26	259.94	150.86	126.74	128.06	117.60
Max	307.59	360.53	184.83	129.55	153.15	154.46

4.2. The Model

As mentioned in the previous section, our empirical strategy exploit the natural random variation in the formation, path and intensity of storms. Given the available data, our model is an unbalanced panel data. We implement a pooled OLS model with year (*i*) and sub-region (*j*) fixed effects following equation 5, where the dependent variable is the natural logarithm of household total or labor income, or whether the household is considered poor or extremely poor (dummy variable). Our identification strategy exploits the variation over time within sub-regions. Results are clustered at the regional level.

$$y_{ijt} = \alpha + \beta H_{jt} + \delta X_{ijt} + \gamma_t + \mu_j + +\varepsilon_{ijt} \qquad (5)$$

Where:

y_{ijt} is labor income, total income, poverty, extreme poverty for household *i* in sub-region *j* and year *t;*
H_{ijt} is the hurricane damage index for major events for sub-region *j* in year *t* (SS ≥ 1);
X_{ijt} is a matrix of control variables at the household level;
γ_t are year fixed effects;
μ_j are country fixed effects.

The model includes rich set of time-varying observable household characteristics (X_{ijt}) such as the maximum level of education of the most educated employed member of the household, access to water and sanitation, crowding,[24] subsistence capacity,[25] and precarious materials.[26] Therefore our estimates are not subject to bias from any unobservable determinant of poverty or income that is time varying but common across all households in Central America.

Our study period in this section involves only 13 years of analysis (2000-2013). Given this shorter period –compared to the nearly 30 years for the per capita GDP analysis– we consider only three events: Hurricane Felix (2008) for Honduras, Hurricane Matthew (2011) for Guatemala and Honduras, and Hurricane Harvey (2012) for Honduras. The three hurricanes are part of SS scale 1, therefore we cannot evaluate the impact of major hurricanes. The other countries (Costa Rica, Panama, and El Salvador) did not have events within our study period and for the years where there is an available and comparable survey.[27]

As discussed in the previous section, wind speed data was aggregated by year. When more than one event occurred in a calendar year in the same country, only the strongest event was taken into account. In this case, we also take into account the time when the household survey was conducted. This is key since household surveys usually record the income of the preceding month. We show two set of results: (i) linearly weighted by the difference between the event's date and the survey's date (divided by 12), and (ii) unweighted results (i.e., regardless of the number of months that have passed since the strongest event). The rationale for this is that the effect of a hurricane on household income (or poverty) might be underestimated if the interval is bigger. Noy (2009) discusses the importance of a weighting function to evaluate impacts on GDP since events observed earlier in the year may have higher impact on GDP than events that occur towards the end of the year.

4.3. Results

Table 5 presents the main results for this section using OLS. Standard errors are clustered at the regional level. Results are standardized in order to render all the indexes comparable. Column (1) – (4) show the non-weighted results, while column (5) – (8) show the (linearly) weighted results. Weighted results are smaller than non-weighted effects. All results include the control variables (maximum level of education, access to water and sanitation, crowding, subsistence capacity, and precarious materials).[28]

Our results show that major hurricanes have substantial adverse impacts on both income and poverty. Based on the non-weighted results, an increase of one standard deviation in the intensity (wind speed) of a hurricane leads to a decrease in total and labor income by 2 – 4 percent, while moderate and extreme poverty increases by 1 – 2 percentage points.

To illustrate these results, we will focus on Hurricane Matthew for Honduran Region 5.[29] According to these parameters, and taking MSWS as a measure of hurricane damage, Hurricane Matthew had a

[24] The ratio of members of the household to the number of exclusive rooms occupied by the household.

[25] Households are considered to have unsatisfied basic needs in subsistence capacity based on two conditions: (i) the ratio of members of the household to the employed members is higher than 3; and (ii) the household head has at most elementary school education.

[26] Where the construction materials of the dwelling are of low quality.

[27] Notice that Hurricane Beta discussed in the second section of the paper is not considered in the analysis because it was a tropical storm when hit Nicaragua.

[28] Results shown in the paper exclude Panama because Panama's observable household characteristics are not available. However results including Panama and without controlling for observable characteristics show similar qualitative results. Results available upon request.

[29] Hurricane Matthew landed in Honduras in 2010 with an SS scale of 2 in the Socio-Economic Region 5 with a Maximum Sustained Wind Speed of 97.92 mph and with and SS scale of 1 in the Socio-Economic Region 2. Hurricane

negative impact of 15.7 percent on per capita labor income, while IHD had an impact of 3.1 percent, while WEI had an impact is of 9.4 percent. The example of Hurricane Matthew reflects the importance of considering a measure of asset exposure in the indexes. The impacts calculated from the levels of the three indicators for Hurricane Matthew reflect a significantly higher impact when considering the MSWS index. Indeed, when considering MSWS, the impact seem to be 5 times higher than the impact calculated from HDI, even if the coefficient estimated within IHD is significantly higher than the coefficient estimated within MSWS. As discussed in Section 2, each indicator relies on different assumptions that may have significant variations. In the particular case of Hurricane Matthew, the lower effect presented by the IHD and WEI indicators appear to indicate an overestimation of the effect when not considering any exposure measure in the MSWS.

Table 5
Impact of Hurricanes on Poverty and Income at the Household Level

	Labor Income	Total Income	Extreme Poverty	Poverty
	Non Weighted Results			
	(1)	(2)	(3)	(4)
MSWS	-0.0300***	-0.0403***	0.0164***	0.0186***
Standard Error	(0.0002)	(0.0002)	(0.0001)	(0.0001)
R-squared	0.430	0.472	0.258	0.317
IDH	-0.0353***	-0.0473***	0.0205***	0.0232***
Standard Error	(0.0002)	(0.0002)	(0.0001)	(0.0001)
R-squared	0.430	0.472	0.258	0.317
WEI	-0.0178***	-0.0243***	0.0100***	0.0119***
Standard Error	(0.0002)	(0.0002)	(0.0001)	(0.0001)
R-squared	0.429	0.471	0.257	0.317
	Weighted Results			
	(5)	(6)	(7)	(8)
MSWS	-0.0159***	-0.0272***	0.00966***	0.0109***
Standard Error	(0.0002)	(0.0001)	(0.0001)	(0.0001)
R-squared	0.429	0.472	0.257	0.316
IDH	-0.0108***	-0.0203***	0.00754***	0.00883***
Standard Error	(0.0002)	(0.0001)	(0.0001)	(0.0001)
R-squared	0.429	0.471	0.257	0.316
WEI	-0.00908***	-0.0170***	0.00592***	0.00704***
Standard Error	(0.0002)	(0.0001)	(0.0001)	(0.0001)
R-squared	0.429	0.471	0.257	0.316

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the sub-regional level.

Matthew landed also in Guatemala with a SS scale of 1 in outside the Metropolitan Region with a Maximum Sustained Wind Speed of 81.64 mph.

Finally, we evaluate heterogeneous responses.[30] It is unclear whether the impact is higher (or lower) in urban or rural areas. In principle, people tend to concentrate in urban areas, which could mean that aggregated impacts could be higher in urban areas. However, at the household level, the effects will depend on the level of assets and on the capacity to minimize the effect of adverse natural events. Dividing our sample by urban/rural our results show that the impact of major hurricanes on rural households is higher than on urban households in terms of income (both labor and total) and in terms of poverty (see Table 6). Impact in rural areas nearly doubles those than in urban areas. Results are stronger when considering MSWS or IDH. In the case of WEI, however, results are likely to be more similar by urban/rural categories.

Table 6
Heterogeneous Impacts of Hurricanes on Poverty and Income by Urban/Rural

	Rural				Urban			
	Labor Income	Total Income	Extreme Poverty	Poverty	Labor Income	Total Income	Extreme Poverty	Poverty
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MSWS	-0.0466***	-0.0622***	0.0219***	0.0248***	-0.0230***	-0.0358***	0.0152***	0.0175***
Standard Error	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
R-squared	0.330	0.371	0.234	0.277	0.398	0.438	0.158	0.234
IDH	-0.0644***	-0.0831***	0.0315***	0.0368***	-0.0201***	-0.0336***	0.0155***	0.0170***
Standard Error	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
R-squared	0.330	0.371	0.235	0.277	0.398	0.438	0.158	0.234
WEI	-0.0253***	-0.0346***	0.0115***	0.0144***	-0.0162***	-0.0263***	0.0115***	0.0129***
Standard Error	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
R-squared	0.330	0.370	0.233	0.276	0.398	0.438	0.157	0.234

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the sub-regional level.

We also divide our sample by the gender of the household head (see Table 7). Our results are not conclusive. Just considering MSWS and IDH, labor income tends to be more affected on female-headed households, while total income tends to be more affected on male-headed households. These differences vanishes when looking at poverty impacts. As in the previous table, results for WEI are more similar across all outcomes. Therefore, we cannot conclude conclusively the existence of differential effects.

[30] Results shown in Table 6-7 are non-weighted. Weighted results provide similar conclusions (not shown and available upon request).

Table 7
Heterogeneous Impacts of Hurricanes on Poverty and Income by Male/Female

	Male-headed households				Female-headed households			
	Labor Income	Total Income	Extreme Poverty	Poverty	Labor Income	Total Income	Extreme Poverty	Poverty
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MSWS	-0.0234***	-0.0454***	0.0183***	0.0204***	-0.0321***	-0.0380***	0.0161***	0.0181***
Standard Error	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.00001)	(0.00001)
R-squared	0.399	0.453	0.211	0.277	0.448	0.478	0.272	0.330
IDH	-0.0249***	-0.0500***	0.0227***	0.0233***	-0.0402***	-0.0461***	0.0203***	0.0236***
Standard Error	(0.0004)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.00001)	(0.00001)
R-squared	0.399	0.453	0.212	0.277	0.448	0.478	0.272	0.330
WEI	-0.0164***	-0.0308***	0.0121***	0.0145***	-0.0178***	-0.0217***	0.00963***	0.0111***
Standard Error	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.00001)	(0.00001)
R-squared	0.398	0.452	0.211	0.277	0.448	0.478	0.271	0.329

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the sub-regional level.

5. CONCLUSION

Although Central America's recent good economic performance has enabled a sustained reduction of poverty, a large percentage of its population is still battling poverty and extremely vulnerable to natural disasters. This means that gains are threatened and could be wiped out in the aftermath of a major disaster. A better understanding of the impacts and potential coping mechanisms is valuable input to inform poverty reduction strategies and policies taking into consideration disaster and climate risk management considerations.

Overall, the methodology of this study improves our understanding on how we model impacts and economic outcomes in Central America, providing a systematic approach to quantifying the effects of disasters on poverty and other well-being indicators in the region. The comparative approach, in terms of hurricane damage indexes, provides a better understanding of how windstorm could impact economic and social outcomes.

One of the key innovations of this study has to do with the use of an accurate and comprehensive model that generates high-resolution, surface-level, sustained wind speed data of historic hurricanes and tropical storms in Central America proposed by Pita el al. (2015). The windstorm model was calibrated and validated for Central America, enabling a more accurate spatial specification and precise inland measures of wind speed. The three hurricane damage indexes (MSWS – unweighted wind speed, IHD – population-weighted index, and WEI – area-weighted index) showcase different aspects of hurricane damage, however all three indexes provide similar conclusions in terms of the negative impacts in GDP per capita, income, and poverty. Results vary slightly across each index but are not statistically different.

The GDP per capita and household analysis complement each other. While data for GDP per capita have been of better quality and statistical significance, they underestimate the effects of hurricane windstorm on the most vulnerable population. GDP per capita does not begin to capture the impact on well-being resulting from these natural hazard events. It requires the combined insight from both sets of analyses to contribute to improve the design of programs and policies, which could then be aimed more effectively at protecting the communities in these countries and increasing resilience, particularly of those in the lowest socioeconomic strata.

Results for the GDP per capita analysis show robust, statistically significant effects in the short term with the three hurricane damage indexes modelling different specifications. The household analysis, on the other hand, despite data limitations, gives an insight into the household characteristics that contribute to dealing with hurricane windstorm risk better. The data for the household analysis, however, has important drawbacks, particularly in terms of time coverage, and is more difficult to handle for comparability purposes.

An interesting area for future research has to do with the long-term cumulative effects of hurricanes. In the literature there is no consensus on whether there are long-term impacts in the national economy as well than at the household level. A more detailed analysis on long-term impact of hurricanes for Central America on the determinants of economic growth and social progress in the region could be valuable. Moreover, the challenge is also in quantifying the indirect effects of disasters. Estimating both direct and indirect economic effects of disasters is central to designing effective DRM policies to support the most vulnerable population in a more efficient way. The effects of adverse natural events impact upon a variety of human welfare indicators and these effects add up. Furthermore, a discussion regarding coping mechanisms would also be relevant. Understanding how households exposed to natural events make decisions, the context in which these decisions are made, and other behavioral elements, could help identify and better characterize their coping mechanisms, resilience levels, and mitigation strategies. Understanding this is paramount in designing effective risk managing strategies. Qualitative research plays an important role in this particular set of questions and could complement quantitative analysis, enriching the lessons learned along the way.

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