The Economic Impact of Hurricanes on Caribbean Agricultural Exports

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Natural disasters can cause severe disruptions to international trade patterns. Nevertheless, in the literature there is hardly any quantitative assessment of this. In this paper we use actual hurricane track data from the National Hurricane Center’s (NHC) “best track” data set in conjunction with agricultural export data from the United Nation’s Food and Agriculture Organization (UNFAO) to evaluate using econometric techniques the potential destruction of hurricanes on Caribbean exports for the period 1961 to 2009. More generally, our results provide unprecedented quantitative economic insight into how natural disasters affect exports.

JEL Classification: Q17; Q54; F10

Key words: Exports, Natural disasters, Windfield model
1. Introduction

Natural disasters can reduce the productive capacity of a country by destroying its physical and human capital together with trade infrastructure negatively affecting exports. Particularly alarming in this regard is that the frequency and intensity of such destructive catastrophes have been rising and their recurrence often tends to be concentrated in particular geographic regions, striking certain countries over and over, with enormous strength to completely destroy entire export sectors. For example, Grenada has been struck by tropical storm Lili in 2002 and hurricanes Ivan and Emily in 2004 and 2005 wiping out 90% of the islands nutmeg and mace tress which at the time contributed 22.5% of its merchandise export.¹ While in 2007 hurricane Dean obliterated 80% to 100% of the banana crop in St. Lucia, Martinique, Dominica and Guadeloupe where replanting and rehabilitation of the industry will take several years.²

Nevertheless despite the large-scale devastation to a country’s exports caused by natural hazards studies in this area have been limited. Instead, by and large the majority of academic papers concentrate more broadly on their macroeconomic impacts particularly focusing on the impact on GDP growth. Noy (2008) summarizes the theoretical literature on the growth implications of natural disasters. These studies all agree that natural calamities negatively affect macroeconomic variables immediately after they strike. In the short and long term the majority of them argue that post disaster economic performance is worst than what was initially forecasted while few concur that there is no negative effect in the year or years following a disaster and projected GDP may even be exceeded.³ In this regard, the macroeconomic effects of disasters may not be easily estimated for a number of reasons. Natural disasters are generally localized events that affect only a small part of the entire economy (Horwich 2000). Additionally, if GDP is taken as the measure of output, after a disaster strikes it may actually increase by the replacement of capital and relief and cleanup activities (Horwich 2000). Moreover, natural disasters may serve as an opportunity for re-investment and replacement of capital goods which can positively affect

growth (Hallegate 2006). As well, there are few studies on the effects of disasters on death toll and demographic trends.  

Another aspect of the literature on natural disasters is that small developing nations are particularly vulnerable as they experience a higher frequency of disasters and have less resources to cope with the after effects and are less likely to return to a path of pre disaster growth. For instance, the islands of the Eastern Caribbean have been singled out as the most disaster-prone territory in the world on account of the large number of hurricane strikes experienced; further “since 1970 a natural disaster inflicting damage equivalent to more than 2% of GDP can be expected” (Rasmussen 2004, p3). Furthermore, although disasters affect all countries their macroeconomic impacts as well as the number of people affected are proportionately larger in small developing economies. For example, the Kobe earthquake of 1995 destroyed physical assets valued at about 2.5% of Japan’s GDP compared to the 2010 Haitian earthquake which wiped out 125% of GDP. Similarly, the Haitian earthquake took 240,000 human lives whereas the geologically more powerful Chilean earthquake a month later killed 500 persons. Lastly, the majority of the population and economic activity tends to be clustered close to the coast line in small countries (McGranaham et al 2007).

With regard to exports, small states often adopt export-led growth as its primary development strategy. Exports play an important role in economic growth through increased capacity utilization, economies of scale, technological progress, employment, labour productivity, resource allocation, foreign exchange earnings and total factor productivity (World Bank 1993). However, despite depending heavily on exports small nations tend to be poorly diversified and their primary exports are agriculture and tourism; two sectors particularly sensitive to extreme weather events (Pelling et al. 2002 and Heger et al. 2008). Also, small island states have fewer infrastructure such as ports and roads and can disproportionately affect exports when compared to larger countries (da Silva and Cernat 2012). In addition, given that small countries are large importers disasters could lead to balance of payments deficits, challenging long-term development efforts. Gassebner et al. (2010) one of the few studies on trade flows and disasters use a gravity model for 170 countries for the period 1962 to 2004 and found that, for a small

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5 Noy (2011).
open developing country, disasters have a negative impact on exports and a positive effect on imports; they gave the case that in 2001, all else being equal a disastrous event in Costa Rica would result in a reduction of exports by 3.9% and an increase in imports by 3.2%.

Moreover, the primary export earner of small developing countries is agriculture. To cite some figures in Antigua and Barbuda, Belize, Guyana and Panama more than 50% of their merchandise exports comprises of food exports while for Aruba, Nicaragua and St. Vincent and the Grenadines this figure is above 80% (WDI 2010). Further, the agriculture sector constitutes a significant portion of the workforce the majority of which tends to be poor. In Jamaica, Panama and Cuba agriculture employs approximately 20% of the workforce in (WDI 2010). As well, the majority of these countries were former colonies whose sole purpose was to supply agricultural raw materials to the imperial powers and as such continue to export these types of products. Lastly, data for the agriculture sector also goes back to the 1960s compared to other sectors as a consequence.

In this paper we provide what we believe to be the first statistical study of the economic impact of hurricanes on exports. Agricultural output is sometimes recommended as a measure of a country’s vulnerability to natural disasters (UNDESA 1999 and Crowards 2000). Moreover, hurricanes are ranked as one of the most deadly and costly natural disasters in the world, and their destructiveness, in particular in the Caribbean region, have been increasing. Specifically we estimate the quantitative impact of hurricane strikes on the small developing countries of the Caribbean over the 1961 to 2009 period. To this end we use actual hurricane track data from the National Hurricane Center’s (NHC) “best track” data set together with agricultural export data from the United Nation’s Food and Agriculture Organization (UNFAO).

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6 Direct impacts of natural hazards on agriculture include loss of crops and livestock, water contamination, increased susceptibility to disease, damage to farm machinery, irrigation systems, transport structures and other agriculture infrastructure. These impacts are often not only felt in the year a disaster strikes but can last up to 2 to 3 years.
7 Emanuel (2003) provides examples of deadly and costly hurricanes in the Atlantic basin.
8 Emanuel’s (2005) index of the potential destructiveness of tropical cyclones has shown increasing storm lifetimes and intensities; Goldenberg et al. (2001) found a 2.5 fold increase in strong hurricanes worldwide and a 5 fold increase in the Caribbean; Elsner et al. (2008) found that the largest upward trends in wind speed exists in the North Atlantic. Warmer oceans with more energy to convert tropical cyclone wind are responsible for the increasing strength of hurricanes.
The remainder of the paper is organized as follows. Section 2 outlines the data sources used, section 3 our methodology. Section 4 presents the results of our analysis. Finally, section 5 concludes.

2. Data

a. Agriculture Export Data

The export data is taken from UNFAO which is the largest, timeliest and most comprehensive agriculture data base globally. It gives detailed agricultural export data (575 products) by value and volume and by country and product from 1961 to 2009 for 245 countries. We employ agriculture export data by volume, which are given in tonnes. Given the data available we are able to construct a sample of 24 countries in the Central American and Caribbean region for the period 1961 to 2009.

b. Hurricane Data

Tropical storm incidents are identified using information from HURDAT, the NHC’s “best track” data set, which provides 6 hourly reports of storm positions and maximum wind speeds of all known tropical cyclones in the North Atlantic Basin. More precisely, for each storm we would like to know if they approached or made landfall in the countries in the region with sufficient strength to potentially cause damage. To do so we construct a hurricane destruction index described in the following section, which use wind speed to measure the potential destruction caused by tropical cyclones. We consider the hurricane destruction index to be a more scientifically based index of potential local destruction. It employs a wind field model on hurricane track data to arrive at potential destruction and allows us to identify damages at a detailed geographical level, compare hurricanes’ destructiveness, and identify the economies most affected, without having to rely on potentially questionable monetary loss estimates provide by insurance companies. More specifically, our hurricane wind damage index is based on being able to estimate local wind speeds at any particular locality where a hurricane strength tropical storm passes over or nearby.

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9 The original list of storms in HURDAT originally started in 1886. This was then extended in 2000 back to 1851, see [http://www.aoml.noaa.gov/hrd/hurdat/Documentation.html#Partagas](http://www.aoml.noaa.gov/hrd/hurdat/Documentation.html#Partagas).
c. Population Data

The population data used is taken from the Latin America and Caribbean Population Database (LACPD), which provides data on the spatial distribution of the region for 2.5 minute grid cells for 1960, 1970, 1980, 1990, and 2000. One may want to note that this breaks the region into 137,820 cells. We use this regional breakdown as the benchmark geographical schemata for our analysis. In order to derive annual national population share figures for each grid cell for each country in our analysis, we used an inter-censal growth rate to interpolate data for years between the given values. It must be pointed out, however, that while the attraction of the LACPD is its spatial richness, the estimates for the early years are likely to be characterized by greater measurement error than those from 1990 onward. More specifically, the LACPD was compiled from maps at the country and sub-national level, national population censuses and United Nations data for the smaller islands of the Caribbean and then interpolated into the grid cell level using information on accessibility as determined by transportation networks. In this regard, information on grid level population distributions were mostly based on censuses from the 1990s and then projected backward based on historical growth rates at larger administrative levels. Moreover, the grid level estimates may be less accurate where large areas are uninhabitable, although this weakness seems to be less of a problem for the region.

[See http://na.unep.net/globalpop/lac/intro.html.]
[For the years prior to (after) the data we simply used the same annual growth rate of the decade after (prior to) it.]
[See http://gisweb.ciat.cgiar.org/population/report.htm.]
3. Methodology

a. The Hurricane Destruction Index

In the literature the extent of potential damages caused by hurricanes is typically measured by wind speed although other factors, such as the slope of the continental shelf and the shape of the coastline in the landfall region in the case of storm surges can play a role.\textsuperscript{13} We use the meteorological wind field model developed by Boose et al. (2004), which provides estimates of wind field velocity of any point relative to the ‘eye’ of the hurricane. This model is based on Holland’s (1980) well known equation for cyclostrophic wind and sustained wind velocity at any point \( P \) is estimated as:

\[
V_r = F \left[ V_m - S(1 - \sin(T)) \frac{V_h}{2} \left( \frac{R_m}{R} \right)^2 \exp \left( 1 - \left( \frac{R_m}{R} \right)^2 \right) \right]^{\frac{1}{2}}
\]

where \( V_m \) is the maximum sustained wind velocity anywhere in the hurricane, \( T \) is the clockwise angle between the forward path of the hurricane and a radial line from the hurricane center to the point of interest, \( P \), \( V_h \) is the forward velocity of the hurricane, \( R_m \) is the radius of maximum winds, and \( R \) is the radial distance from the center of the hurricane to point \( P \). Of the remaining ingredients \( F \) is the scaling parameter for effects of surface friction, \( S \) the scaling parameter for asymmetry due to the forward motion of the storm, and \( B \) the scaling parameter controlling the shape of the wind profile curve. The peak wind gust velocity at point \( P \) can then be estimated via:

\[
V_g = GV_s
\]

where \( G \) is the gust wind factor.

The next step entails translating these wind field calculations into potential damage estimates. As noted by Emanuel (2005), both the monetary losses in hurricanes as well as the power

\textsuperscript{13}
dissipation of these storms tend to rise roughly as the cube of the maximum observed wind speed rises. Consequently, he proposes a simplified power dissipation index that can serve to measure the potential destructiveness of hurricanes as:

\[
PDI = \int_0^r V^3 dt
\]  

(3)

where \( V \) is the maximum sustained wind speed, and \( \tau \) is the lifetime of the storm as accumulated over time intervals \( t \). Here we modify this index to obtain an index of potential damage of a hurricane at a particular spatial locality. More precisely, the total destruction due to a storm \( r \) in country \( i \) at locality \( j \) in year \( t \) is:

\[
HD_{ij,r,t} = \sum_0^r V_{i,j,r,t}^3 \quad \text{if } V \geq 119 \text{ km/hr}
\]  

(4)

The index in (4) can then be used to calculate annual total destruction in local \( j \) by aggregating all its values over a year \( t \).

See Strobl (2012) for full details on the hurricane destruction index.

b. Regression Analysis

The aim of our paper is to estimate the impact of hurricanes on agriculture exports for 24 countries in the Central American and Caribbean region from 1961 to 2009. To accomplish this we employ the following model specification:

\[
\text{EXPORT}_{it} = \alpha + \beta H_{it} + \mu_i + \lambda_t + \epsilon_{it}
\]  

(1)

where \( \text{EXPORT} \) is the volume of exports (in metric tonnes) exported from locality \( i \) in year \( t \), \( H \) is our hurricane index of potential destruction affecting locality \( i \) in year \( t \), and \( \beta \) is our coefficient of interest. \( H \) takes the form of three indices and includes all the wind speeds that we classify as hurricanes within the 500km of any population point in the region. If the storm is at least a category 1 hurricane we calculate our wind speed for each grid cell in the population data. In many cases this is zero (because they are too far away or too weak), but for when it is not we categorize these into three indices: (a) one that includes all positive wind speed cells, no matter what wind speed; (b) one for when the wind speed is above 119km/hour, otherwise we set
it to zero; and (c) one for which the wind speed is above 178km/hour otherwise we set it to zero. The regression equation is therefore run with each index separately.

One should note that via $\mu$ we also allow for any time invariant country specific factors that determine exports but may also be related to tropical cyclone strikes in country $i$, and hence the exclusion of which may result in biased estimates of $\beta$. For example, one might suspect that countries that are more likely to be affected by hurricanes may subsequently be relatively less likely to export agriculture products. In order to take account of these time invariant unobservables we employ a fixed effects estimator which essentially transforms all variables into deviations from their means and hence purges $\mu$ from the specification.\textsuperscript{14} We also allow for year specific effects $\lambda$ that are common to all localities but may also be correlated with export figures by including a set of year dummies.

A particular concern with agricultural data is that of serial correlation\textsuperscript{15} and given that the data is at individual product lines another factor to consider is cross-sectional dependence.\textsuperscript{16} We therefore employ an estimator that allows for arbitrary cross correlation and serial correlation developed by Hoechle (2007) to obtain Newey-West standard errors. There is assumed correlation of errors between panels or spatial correlation while auto-correlation within panels is assumed to be of the general-form rather than AR (1).\textsuperscript{17} This estimator assumes heteroscedasticity and autocorrelation up to some lag and possibly correlated between the panels and is therefore favored over other panel estimators such as and as it generates Driscoll and Kraay (1998) standard errors which account for within-group correlation, heteroscedasticity and cross-sectional correlation that are very robust to general forms of cross-sectional and temporal dependence. Inclusion of time dummies in the regression captures cross-sectional dependency when the time effect is common to all countries. However, when there are other forms of cross-sectional dependency as in our case cross-sectional correlations are not the same for each pair of

\textsuperscript{14} Likewise a set of country dummy variables could have been included.
\textsuperscript{15} A serial correlation test allowing for fixed effects. Woolridge (2002) provides full details.
\textsuperscript{16} A test for cross-sectional dependence is the Breusch-Pagan test. However, this test is not applicable when the number of groups is greater than the number of years in the panel. When this occurs a test by Pesaran (2004) is used. For both tests, if the null hypothesis is rejected, one can conclude that the error terms are dependent across countries. See Greene (2000) for details.
\textsuperscript{17} The xtscc program default for selecting m(T) when no lag(#) option is specified is to use the first step of Newey and West’s (1994) plug-in procedure that sets m(T) = floor[4(T/100)^{2/9}]. The limitation however, is that the lag length may not be optimal because this procedure is essentially independent from the underlying data and may choose a lag length that is too small. There is however no superior alternative.
countries and the inclusion of time effects does not significantly change the point estimates of the other coefficients.

4. Results

We run our regression equation using the three hurricane indices separately which we calculate for at least a category 1 hurricane. The first index is therefore all positive wind speed cells, if the storm is at least a category 1 hurricane the second is where the wind speed is above 119km/hour, otherwise we set it to zero and thirdly where the wind speed is above 178km/hour otherwise we set it to zero. Also, for each index we include lags to determine whether the impact is short or long term. Further, our estimations are done at the aggregate level to estimate the impact on total exports as well as the product level to see the outcome on individual product lines.

Consequently, the results show (table A2 in the appendix) that the damage caused by hurricanes is estimated to have a significant and negative impact on exports in the year that they strike and in the year following\(^\text{18}\) both at the aggregate and product levels. Using the first index we can say that in general hurricanes have a downward effect of 0.0068 tonnes in the year that they strike and 0.0049 tonnes in the year following a strike at the aggregate level. The equivalent figures at the individual product level are much smaller at .000029 and .000019 tonnes respectively. Using wind speeds above 119km/hour the destruction at the aggregate level is .00676 tonnes in the year of a strike and 0.00653 tonnes in the year following. Similarly for the product level the damage is 0.000033 and 0.000033 tonnes respectively. For wind speeds above 178km/hour the destruction at the aggregate level is 0.0064 tonnes in the year of a strike and 0.0069 tonnes in the year following. In terms of the product level these figures are 0.000029 and 0.000031 tonnes respectively.

\(^{18}\) The negative effect does not go beyond the second year; a third lag was included and was found to be insignificant.
5. Conclusion

Natural disasters cause severe disruptions to a country’s exports particularly agricultural exports. These effects are amplified in small developing states where most depend on exports as their primary growth strategy. In this paper we estimated the impact of hurricanes on exports using 24 countries from the Caribbean and Central American region over the period 1961 to 2009 using UNFAO export data as well as a hurricane potential destruction index. We show that in general hurricanes reduce agriculture exports by 0.0068 tonnes in the year that they strike and 0.0049 tonnes in the year following a strike.
References


**Appendix**

**Table 1: Summary Statistics**

<table>
<thead>
<tr>
<th>Countries</th>
<th>ISOCODE</th>
<th>UNFAO data</th>
<th># of Hurricanes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aruba</td>
<td>ABW</td>
<td>1986-2009</td>
<td>10</td>
</tr>
<tr>
<td>Netherland Antilles</td>
<td>ANT</td>
<td>1961-2009</td>
<td>12</td>
</tr>
<tr>
<td>Antigua and Barbuda</td>
<td>ATG</td>
<td>1961-2009</td>
<td>22</td>
</tr>
<tr>
<td>Bahamas</td>
<td>BHS</td>
<td>1961-2009</td>
<td>31</td>
</tr>
<tr>
<td>Belize</td>
<td>BLZ</td>
<td>1961-2009</td>
<td>18</td>
</tr>
<tr>
<td>Bermuda</td>
<td>BMU</td>
<td>1972-2009</td>
<td>3</td>
</tr>
<tr>
<td>Barbados</td>
<td>BRB</td>
<td>1961-2009</td>
<td>17</td>
</tr>
<tr>
<td>Costa Rica</td>
<td>CRI</td>
<td>1961-2009</td>
<td>6</td>
</tr>
<tr>
<td>Cuba</td>
<td>CUB</td>
<td>1961-2009</td>
<td>34</td>
</tr>
<tr>
<td>Dominica</td>
<td>DMA</td>
<td>1961-2009</td>
<td>22</td>
</tr>
<tr>
<td>Dominican Republic</td>
<td>DOM</td>
<td>1961-2009</td>
<td>27</td>
</tr>
<tr>
<td>Grenada</td>
<td>GRD</td>
<td>1961-2008</td>
<td>17</td>
</tr>
<tr>
<td>Guatemala</td>
<td>GTM</td>
<td>1961-2009</td>
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</tr>
<tr>
<td>Honduras</td>
<td>HND</td>
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<td>Haiti</td>
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<td>Jamaica</td>
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<td>25</td>
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<td>St. Kitts and Nevis</td>
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<td>VCT</td>
<td>1961-2009</td>
<td>18</td>
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**Table 2: Regression results, aggregate and individual lines**

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<tr>
<th>H_{1}</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<td>-.0067578</td>
<td>-.0063792</td>
<td>-.0000292</td>
<td>-.0000331</td>
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<tr>
<td>(.0039523)*</td>
<td>(.0026456)**</td>
<td>(.002975)**</td>
<td>(.0000154)**</td>
<td>(.0000133)**</td>
<td>(.0000141)**</td>
<td></td>
</tr>
<tr>
<td>H_{1-1}</td>
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<td>-.0065305</td>
<td>-.0069074</td>
<td>-.0000187</td>
<td>-.0000329</td>
<td>-.0000305</td>
</tr>
<tr>
<td>(.003295)</td>
<td>(.0026979)**</td>
<td>(.0032986)**</td>
<td>(.000011)*</td>
<td>(.0000142)**</td>
<td>(.0000143)**</td>
<td></td>
</tr>
<tr>
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<td>.0016831</td>
<td>.0017664</td>
<td>-2.95e-06</td>
<td>.0000116</td>
<td>.0000119</td>
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<tr>
<td>(.0023591)</td>
<td>(.0019743)</td>
<td>(.0018433)</td>
<td>(7.00e-06)</td>
<td>(.000011)</td>
<td>(9.59e-06)</td>
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| Nr. Obs.      | 194099 | 204410 | 204410 |
| Nr. Countries | 24     | 24     | 24     | 24     | 24     | 24     |

13
<table>
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<tr>
<th>F-test $u=0$</th>
<th>71.59***</th>
<th>3725084.65***</th>
<th>2038472.77***</th>
<th>29.21***</th>
<th>519516.42***</th>
<th>13214.10***</th>
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<td>$R^2$ (within)</td>
<td>0.1448</td>
<td>0.1435</td>
<td>0.1357</td>
<td>0.0007</td>
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</table>

Notes: (1) Standard errors in parentheses. (2) ***, ** and * identify 1, 5 and 10 per cent significance levels.