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The Impact of Tropical Storms on Households:

Evidence from Panel Data on Consumption

Abstract

This paper investigates the impact of tropical storms on Jamaican household consumption. We build a panel dataset that follows individual households over time thus enabling us to take account of time invariant household and location unobservables that could be correlated with mean tropical storm exposure. Our results show that while the average damaging hurricane reduces per capita consumption by approximately 1.1 per cent, more destructive events can cause losses multiple times this amount. There are, however, heterogeneous impacts across households, where only those that live in buildings with less wind resistant walls are affected. Additionally, we find that households are able to partially buffer the negative impact on consumption through remittances and savings, as well as by shifting funds away from non-regular expenditures. Again, households differ in the nature of this buffering according to the wind resistance of their buildings.

Words (12,500)

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Section I: Introduction

Tropical storms cause considerable economic losses across the world. For example, estimates on their monetary damages suggest that losses have amounted to over $33 billion since 2000.[1] Worryingly, developing countries are those disproportionately affected by these extreme weather events (Doocy *et al.*, 2013). Moreover, developing countries are unlikely to have the social security safety nets that are typically available in developed countries after a natural disaster; see Deryugina (2017). A growing literature has now investigated what the aggregate wealth implications of tropical storms are, although the conclusions have been rather mixed; see Noy and DuPont (2016) and Klomp and Valckx (2014) for reviews.[2] However, aggregate data may be masking considerable heterogeneity of the impact of these storms across the various actors within an economy. As a matter of fact, in developing countries, it is often households that are vulnerable and of the greatest concern to policymakers due to their inability to cope with negative shocks. Nevertheless, the number of studies that have explicitly investigated the impact of tropical storms, or even natural disasters more generally, on households have been few and their conclusions have varied widely.

A telling insight into the current state of the literature of natural disasters on households is the recent meta-analysis by Karem and Noy (2014). In their review of 38 papers on the topic, the authors conclude that while there is a general tendency to find a negative impact on household welfare[3], this impact appears to be only short-term. Importantly, however, even for those studies that found clear evidence of consumption reduction, the actual quantitative

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[1] Source: Emergency Events Database (EM-DAT)

[2] For instance, Smith (2008), Hisang (2010), Strobl (2011), Strobl (2012), and Elliott *et al.* (2015) find short-term effects, while the study by Hsiang and Jina (2014) shows evidence of a long-term impact.

[3] Note that this literature has used an array of different measures for measuring welfare, including consumption (Kurosaki, 2010; Thomas *et al.*, 2010; Anttila-Hughes and Hsiang, 2012; Arouri *et al.*, 2015; Karim and Noy, 2014), income (Karim and Noy, 2014; Aurori et *al.*, 2015; Ishizawa and Miranda, 2018) and assets (Carter et *al.*, 2007).

extent of these losses differs widely, thus making it difficult to evaluate the urgency of explicitly employing policies to help households deal with these negative shocks.

Even if one explicitly focuses on tropical cyclones, rather than natural disasters in general, it is difficult to draw any conclusions with regard to the impact, at least quantitatively, on household consumption. For example, Thomas *et al.* (2010) and Arouri *et al.* (2015) find that the impact of storms resulted in Vietnamese households experiencing a 52% and 1.5% reduction in consumption with the use of cross-sectional and commune level panel data, respectively. In contrast, provincial panel data for the Philippines show a reduction between 5.9% and 7.1% in consumption (Anttila-Hughes and Hsiang, 2012), while Central American countries experience a decline ranging between 2% and 4% (Ishizawa and Miranda, 2018). Baez *et al.'s* (2015) use of panel data also show a fall in the consumption of Guatemalan households by 12.6%. Thus, these storm-focused studies demonstrate a large disparity in tropical storm impact, making it difficult to draw definitive conclusions on how household consumption is affected.[4]

There could of course be many reasons as to why there is such an array of different results on the household welfare impact of natural disasters in general, and tropical cyclones in particular. Perhaps the most obvious, is the difference in the measurement of tropical cyclone destruction. Earlier studies tended to use storm incidence or wind speed categories (see Thomas *et al.*, 2010 and Arouri *et al.*, 2015). In contrast, more recent papers modeled local damage explicitly with physical wind field models; see, for instance, Strobl (2012) and Ishizawa and Miranda (2018). Importantly, capturing the appropriate functional form of the damage function will reduce measurement error and hence the possibility of attenuation bias.

[4] Note that the discrepancy between long versus short term impacts is also prevalent in studies for developed countries. For instance, Deryugina *et al.* (2018) find a long term impact of Hurricane Katrina on its victims, while Shaughnessy *et al.* (2010) found that the same storm decreased income inequality.

Another potentially important reason is that, as of date, most studies on the impact of tropical storms on household consumption have been restricted to using cross-sectional data.[5] Arguably, however, unless one has a very rich set of controls, not being able to control for household fixed effects can lead to biased estimates, particularly in a household consumption context (Jenkins and Siedler, 2007; Kurosaki, 2010; Aurori *et al.*, 2015). More specifically, households should rationally choose to locate in those areas that are less likely affected by tropical cyclones. However, the ability to do so may be related to other (unobserved) factors that determine consumption. In the only study that used panel household data in a tropical storm context, Baez and Santos (2007) focus on a single event, i.e., the impact of Hurricane Mitchell on Nicaragua, and classify households as being located in affected municipalities or not. In comparing adult share of consumption of tobacco and alcohol, they find that these are not impacted by the storm.[6]

The different results on the effect of tropical cyclones in the literature may also be due to the widely heterogeneous sample of countries examined. In particular, one might suspect that the manner in which households may in the absence of formal insurance mechanism try to buffer these negative shocks could differ substantially across and within countries. Some households may try to smooth their consumption through informal mechanisms such as borrowing, drawing on savings, or the liquidation of assets (Morduch, 1995; Van de Berg and Burger, 2008). However, others without access to these financial funds may have to reallocate their budget to necessary consumption, such as food, from non-food and other non-necessary

[5] The only exception in this regard is Ishizawa and Miranda (2018) in their study of several Central American countries. However, while they use panel data derived from household surveys, the panel is constructed from cross-sectional household level data and aggregated to regional level. They are thus not able to account for household specific fixed effects.

[6] The main focus of the paper is on how the storm affected child vulnerability, and they hence did not explicitly investigate the impact on total household welfare.

expenditure (Skoufias, 2003).[7] Indeed, for natural disasters there is some evidence that households may smooth their food consumption by reducing the consumption of non-food items. Plausibly, not taking account of the complexity of these insurance mechanisms may be a driving factor behind the large variety of results found in the existing empirical literature.

In this study, we attempt to addresses the highlighted potential shortcomings in the existing literature using the case study of household consumption and tropical cyclones in Jamaica. In particular, we build a panel of households for which we can observe households up to 4 years over a 21 year period. This allows us in our econometric analysis to take account of household fixed effects and thus to interpret the tropical cyclone shocks as random realizations of the probability distribution of storms. Additionally, we construct a hurricane damage index that is location specific and based on the physical characteristics of the storm, which some of the more recent literature has shown to be important.[8] We also investigate whether treatment effects are different for households residing in buildings with walls of different wind resistance. Finally, we estimate the importance of both informal insurance mechanisms, as well as the reallocation of consumption across goods, as a way of buffering the negative consequences of cyclone strikes.

For the purpose here, Jamaica is arguably a particularly relevant case to study not only because of data availability, but also because it is subject to frequent tropical storms. For instance, over our sample period, 1990 to 2010, we identified 15 damaging storms. As a matter of fact, Jamaica is ranked number three behind Haiti and the Dominican Republic in terms of the number of storms experienced between 1990 and 2008 (ECLAC, 2010) and is cited as being one of the most vulnerable countries in the Caribbean on the environmental

[7] There are of course many other ways that households have been shown to buffer consumption shocks, such as adjusting their labour supply (Kochar 1999; Garuiglia and Kim, 2003; and Skoufias, 2003) or increasing child labor (Jacoby and Skoufias, 1998).

[8] See, for instance, Strobl (2012) and Spencer, Polachek and Strobl (2016).

vulnerability index (Kaly *et al.*, 2004). Tropical cylcones have at times been detrimental to the Jamaican economy. For example, the most damaging hurricane ever to hit Jamaica in modern times was Gilbert in 1988, causing damages amounting to US$4 billion (Pan American Health Organization, 1988). Other damaging storms were hurricanes Ivan in 2004 and Dean in 2007, where the former resulted in US$139 million damage to the agriculture sector and significant damage to the homes of over 700,000 Jamaicans (Planning Institute of Jamaica (PIOJ), 2004), while the latter generated around US$81 million damage in agriculture with housing suffering over 84% of losses (Planning Institute of Jamaica, 2007).

Our analysis produces a number of interesting findings with considerable relevance to the existing literature. Firstly, we show that not controlling for time invariant unobservables can produce biased estimates of the impact of tropical cyclones on household consumption. We also demonstrate that there are differential treatment effects across household's building type in terms of their wall's wind resistance. Interestingly, our results show that Jamaican households tend to employ both buffering through informal financial mechanisms, such as drawing on savings or receiving remittances, and reallocating budgets across necessary and non-necessary good types as partial coping strategies. More generally, however, in line with most of the literature, the impact on welfare, even for those households that cannot buffer the shocks through financial resources, is short lived, small on average, and only large for the rare extremer events.

The remainder of the paper is organized as follows. In the next section we discuss the data and the construction of the hurricane damage index. Section 3 presents some summary statistics. Section 4 follows with the econometric estimations and results. Section 5 concludes.

Section II: Data and Summary Statistics

II.A. Household Data

Our source of data for Jamaican households is the Jamaica Survey of Living Conditions (JSLC). This survey was first introduced in 1988 and has collected information annually[9] since then, except for 2011.[10] In general, each JSLC questionnaire has included modules on housing, health, education, consumption, and nutrition. Importantly, the JSLC is constructed on a rotating panel basis. More specifically, in those years that the master sampling frame is not updated, half of the households surveyed from the previous year are re-surveyed. On occasion as many as four successive JSLC samples were drawn from the master frame. Overall, the system of rotation of the JSLC enables the construction of panels of households for the periods 1990-1992, 1993-1994, 1995-1996, 1997-1998, 1998-2000, 2002-2003, 2004-2006, and 2007-2010. Given that the sampling is done of dwellings rather than households, we follow the procedure of Handa (2008) to match households across survey rounds.[11] Overall, this allowed us to create an unbalanced panel of 9,553 households, of which the average number of observations was 2.48.

We use the SLC to calculate total consumption (expenditure) per capita. In the data, total consumption can also be decomposed on a consistent basis over surveys in terms of food consumption, non-food consumption, and non-regular consumption. Food consumption consists of fruits, vegetables, protein and all forms of carbohydrate intake, while non-food consumption includes items such as household supplies, electronics, furniture, personal care items, clothing and education expenses. In contrast, non-regular consumption items consist of expenditure on weddings, funerals, gambling, life and general insurance payments, and donations. Per capita values of all these consumption variables are obtained by normalizing by the number of household members. Since the JSLC interviews are conducted during

[9] Originally the JSLC was conceived to be a semi-annual survey but in 1990 annual surveying was deemed to be sufficient.

[10] The JSLC covers on average about 0.3 per cent of total households in Jamaica.

[11] Once a unique household identifier is constructed, households are matched across years if the sex of the household head remained the same, if his/her age did not change by more than 2 years, and if the number of members in the household did not change by more than 2 people. According to this criteria, similar to Handa (2008), our match rate was about two thirds, with slightly higher rates in later years of the sample period.

various months of the year, we use the monthly Consumer Price Index data from STATIN corresponding to the month of the interview to deflate our expenditure variables to 2010 values. In terms of location, we know the enumeration district each household is located in. The spatial breakdown of the 6,327 districts is shown in Figure B1 in Appendix B.

As our main time varying household level control we calculate the share of children,: defined as the proportion less than or equal to 14 years of age in a household.[12] The JSLC also consistently collected information on whether a household received remittances. Specifically, households are asked to indicate yes or no as to whether they received support from specific sources including children, parents, spouse and other relatives living overseas. Finally, we processed information on whether households received interest payments from financial institutions, which we use as an indicator of the existence of savings by the household.

The JSLC also consistently collected information on the main material of the outer walls of the buildings that households reside in. More specifically, the JSLC categorizes the outer main walls of a household's building into 7 main types: wood, stone, brick, concrete nog, block and steel, wattle and adobe, and other.

II.B. Hurricane Destruction Index

While the earlier literature on the economic impact of tropical cyclones used incidence dummies or ex-post damage estimates as proxies of storm destruction, recently it has become much more common to construct a proxy of damages based on the physical characteristics of the event and to allow this to vary across space; see, for instance, Strobl (2012) and Ishizawa

[12] Unfortunately, the JSLC did not consistently collect much more household level information over time that would not be potentially considered as 'bad controls' in the Angrist & Pischke (2009) sense.

and Miranda (2018). More specifically, this approach allows one to take account of the many features of a hurricane that will determine the spatial heterogeneity in wind speeds experienced locally, as, for instance, the position relative to the storm, the maximum wind speed of the storm, the movement of the storm, and landfall.[13]

To construct a hurricane index that takes into account how the features of a storm impact local wind speed, we take a set of households, *i=1,…, I*, located in regions, *j=1,…., J*, that experience a set of hurricanes, *k=1,…, K*, with life times of *s=1,…,S*. Then the hurricane destruction for household *i* during the year *t* is defined as:

$$H_{i,j,t} = \sum_{k=1}^{K}\sum_{s=1}^{S}\left(W_{i,j,k,s,t}\right)^3 \qquad W_{i,j,k,s,t} \geq W_{i,j}^{*} \qquad (1)$$

where *W* is the measured wind speed in region *j* during a storm *k* at point *s* of its life time and *W** is the household specific threshold above which wind is damaging. Thus, the two main required inputs for the construction of the index are *W* and *W**. As can be seen, we allow local destruction to vary with wind speed in a cubic manner since, as noted by Wang and Xu (2010) and Emanuel (2011), kinetic energy from a storm dissipates roughly to the cubic power with respect to wind speed and this energy release scales with the wind pressure acting on a structure. By summing the values of *W* over its life time *s* we account for the duration of exposure. Moreover, we allow for the possibility of more than one damaging storm occurring in a year by using the sum of the cubic value of *W* across storms within years. As a threshold for damage to occur we set *W** at 119 km/hr, which corresponds to the cut-off point for the lowest definition of a hurricane, i.e., a Saffir-Scale of 1. One should note that damage at this level is by the National Hurricane Center (NHS) described as:

[13] Importantly this allows one to take account of the fact that even if storms do not make landfall, they can cause considerable damage due to strong winds.

"Well-constructed frame homes could have damage to roof, shingles, vinyl siding and gutters. Large branches of trees will snap and shallowly rooted trees may be toppled. Extensive damage to power lines and poles likely will result in power outages that could last a few to several days."[14]

As noted above, what level of wind a region *j* will experience during a passing storm, i.e., *W*, depends crucially on that region's position relative to the storm and the storm's movement and features, and thus requires explicit wind field modeling. We use Boose *et al.'s* (2004) version of the well-known Holland (1980) wind field model which, given hurricane track data, can estimate the wind experienced at any local point relative to the storm during its life span. Details of this model are described in detail in Appendix A.

Since the location indicator that we have for households is at the enumeration district level, we use these as our regions, $j=1,\ldots, J$, and calculate the maximum wind speed for each storm relative to each district's centroid. The relevant storms over our sample period that produced local wind speeds of at least 119 km/hr in at least one of the enumeration districts are listed in Table 1. Accordingly, in total there were 15 damaging storms, one of which (Gilbert) made landfall at hurricane strength. These storms were not evenly distributed over years, with 2005 and 2008 experiencing the most incidences. We depict their tracks in Figure 1.

It is important to point out that *H* is constructed taking into consideration the month of interview of households. More specifically, households are potentially interviewed during different months in a year. Thus in constructing *H* at time *t* for household *i* we consider the hurricane events that took place within the twelve months of household *i*'s interview month. Hence, even two households within the same enumeration district may have different measures of *H* if they were interviewed in different months. One may want to note that *H*

[14] See https://www.nhc.noaa.gov/aboutsshws.php.

does not have a straightforward interpretation. Rather it can be considered as the sum of energy dissipated during a storm, measured in km per hour.

II.C. Other Climatic Controls

Since, as noted by Auffhammer *et al.* (2013), tropical cyclones could be correlated with other climatic aspects that in our context may also affect household's economic consumption, we also construct a number of other climatic controls. More specifically, we took information from the Climatic Research Unit (CRU) TS v. 3.24 dataset compiled by the CRU at the University of East Anglia, which provides monthly precipitation and average temperatures at the 0.5×0.5 degree resolution globally for land surface areas. The relevant cells were masked out for Jamaica and then each district attributed to the weather cell centroid it was closest to. We then constructed monthly average rainfall and temperature for each enumeration district.

II.D. Summary Statistics

Table 2 provides descriptive statistics for all variables used in our analysis. As can be seen, mean consumption per capita is about J$16,000. The distribution of consumption per capita is also shown in Figure B2 in Appendix B, along with the official poverty line (J$21,895 – see PIOJ, 2011). Accordingly, about 17.6% are below the poverty line. In term of consumption components, food has the largest average share (0.61), followed by non-food (0.36), and non-regular (0.03) consumption. The mean household has an average share of children of 26 per cent. Remittances and interest receipts from loans average around 0.55 and 0.05, respectively. Finally, the mean value of our hurricane index when it takes on non-zero values, i.e., when it is damaging, is 0.37 (normalized by 1.0e+09).[15]

Section III: Econometric Estimation and Results

[15] For example, if a district experienced wind speeds above 119 km/hr for 24 hours, changing from 119km/hr in the first 12 hours, to 200km/hr during the subsequent 8 hours, and to 121km/hr in the final four hours, then the index would be: $(12*119^3 + 8*200^3 + 4*121^3)/1.0e+09=0.913$.

III.A Econometric Specification

Our task is to determine the impact of hurricane destruction on household per captia consumption as follows:

$$log(C_{ijt}) = \alpha + \beta_1 H_{ijt} + \beta_2 X_{ijt} + m_{it} + \lambda_t + \mu_i + \varepsilon_{ijt} \qquad (2)$$

where C_{ijt}, is total consumption per capita for household i, district j and year t, H_{ijt} is the household specific hurricane destruction index defined in (1), X is a vector of household and climatic controls, namely share of children in the household and mean (over the year) monthly rainfall and temperature, m are interview month indicators, λ are year dummies, and μ time invariant household specific unobservables possibly correlated with our other explanatory variables. Note that we divide H through by 1.0e+09 so as to make the estimates more readable.

An important aspect to consider is how to calculate the standard errors, given that treatment will be correlated across households. If this is not taken into account then the estimate could be biased downward.[16] As noted by Schlenker and Roberts (2009) and Hsiang (2016), this may be particularly a problem when examining the effect of climatic phenomena, which are likely to be spatially correlated. They both suggest explicitly modeling this spatial dependence. The choice then is how far this spatial correlation reaches. One challenge in this regard with respect to storms is that they can differ in size and local effects. We thus identified the enumeration districts affected in each of the storms over our sample period, and calculated the distances between these. This was on average about 60 km, and thus we used this as a 'natural' benchmark threshold distance within which to model spatial dependence, employing the approach by Hsiang (2010).

[16] See Bertrand *et al*. (2004).

III.B Total Consumption

We first estimate the impact of hurricanes on total consumption expenditure per capita without controlling for household fixed effects, μ, and other controls, as shown in the first column of Table 3. This produces a negative but insignificant coefficient on *H*, suggesting that there is no impact on household consumption. We next included our climatic controls, rainfall and temperature, as well as the share of children in the household, as controls. While the coefficient, depicted in the second column, increases fourfold it remains insignificant.

As discussed earlier, there may be other unobserved aspects of a household that are correlated with their mean hurricane exposure, such as choice of location.[17] In the third column of Table 3 we re-estimate the specification in the second column but now also control for household fixed effects. Accordingly, this produces a negative and statistically significant effect and suggests that not being able to control for time invariant observables in cross-sectional data may substantially underestimate the impact of tropical storm damage on household consumption. Using the estimated coefficient and multiplying this by the mean non-zero value of *H* suggests that when a damaging hurricane occurs consumption falls by about 1.1 per cent.[18] This result can also be considered in terms of its implications for poverty in Jamaica. For example, in 2010 about 12 per cent of households would be considered to be below the poverty line.[19] An average size hurricane would consequently, taking into consideration the distribution of wall types, make about a further 1 per cent of households temporarily poor.

[17] To document whether poorer HHs locate in more hurricane prone areas, we proceeded as follow. We ran our wind field model for storms going back to 1855 at the enumeration district level and then for each district calculated out the number of incidences of storms that caused local wind speeds greater than 119 km/hr. We merged this data with the average income per capita derived from the (exhaustive) 2011 Census per household. The correlation was positive and statistically significant, although only 0.08.

[18] Since consumption is logged, the effect in percentage terms is simply $H*\beta_H$, for any chosen value of *H*. For example, for the mean non-zero value of *H_WEAK*, this would simply be 0.57*0.019=0.01083.

[19] The official poverty line in Jamaica is 12,000 per capita Jamaican dollars.

One should note that our estimated effect is smaller than the average impact of between 5.9 and 7.1 per cent that Antilla-Hughes and Hsiang (2012) find for the Philippines. However, given that the authors cannot control for household fixed effects, some caution must be drawn in making such a direct comparison. In their study of the impact of the strongest tropical cyclone ever to strike Guatemala in modern times, Baez *et al.* (2015) find that the impact on per capita consumption was 12.6 per cent. This is more than double the implied impact (5.2 per cent) of the largest observed value of our damage index over our sample period, which implied a 5.5 percentage rise in poverty. While not within the context of natural disasters, Beegle *et al.* (2008) find using a panel of Tanzanian households that adult mortality shocks cause consumption to drop by about 7 per cent.

One should note that the estimated coefficient on *H* thus far captures the `average treatment' effect of hurricane damages on household consumption. However, households may differ widely in their vulnerability. For example, one important factor is the type of dwelling they are residing in, where the material of the outer walls is crucial in terms of a building's resistance to tropical cyclone winds. As a matter of fact, in an extensive study of common building and wall types and their resistance to hurricane winds in Jamaica, the Agency for International Development (1981) identified a number of outer wall types that were substantially more vulnerable to hurricane wind exposure. More specifically, housing made of wattle and daub, concrete nog, or wood, or some combination of these types was found to be especially vulnerable. We thus define households as residing in hurricane wind weakly resistant housing if the outer walls of their building consists of these types and strongly resistant otherwise.[20] In our matched panel sample, 37 per cent of households accordingly reside in buildings that are weakly resistant to hurricane winds. Also, over our

[20]The importance of modeling differences in vulnerabilities across building types in this manner was previously demonstrated by Unanwa *et al.* (2000) using damage and wind exposure information gathered from a large number of studies for the US.

sample period the proportion of households living in weakly resistant housing has fallen considerably from 53 to 28 per cent. Importantly, one should note that we are not able to disentangle the use of wind resistant walls from other factors that could be correlated with household consumption and living in an area that is on average more exposed to hurricane damage. Thus, while the hurricane shocks themselves - after controlling for household fixed effects - can be considered exogenous, any differences in consumption response to hurricane damages across wall types cannot be strictly interpreted causally.

We next used our building classification to create dummies for strong and weak wall type households and interacted these with *H* to create two interaction terms, *H_WEAK* and *H_STRONG*. This allow us to disentangle the heterogenous treatment effects of *H* across these two household types, where results using a fixed effects model with our time varying controls are depicted in the fourth column of Table 3. Accordingly, we find a negative and significant impact of hurricane destruction for weak walled households, while the negative impact for those households residing in more wind resistant buildings is insignificant. This possibly suggests that only households in weakly resistant housing reduce their consumption after a damaging hurricane, although one should note it may also be a result of insufficient power.[21] Using the estimated coefficient and multiplying this by the mean non-zero value of *H_WEAK* suggests that when a damaging hurricane occurs consumption rises by about 1.2 per cent. The largest observed value of damage, as occurred during Hurricane Ivan, indicates a fall of 15.8 per cent in per capita consumption.

In the fifth and sixth columns of Table 3 we investigated whether there were any longer-term effects of storms on household consumption. However, as can be seen, while the contemporaneous impact for weaker wall households remains, there is no evidence of a

[21] A joint test of significance implied that the two coefficients were jointly significant at the five per cent level.

lagged (or delayed) effect for either group.[22] Thus we find only a short-lived effect of hurricanes on household consumption in Jamaica, a result that has been echoed in at least some of the other household level studies, as outlined earlier.

Given the heterogeneous impacts across building wall classification, we, for the rest of the analysis, continue to decompose the impact of hurricanes across these two household types. The full set of results for this, our benchmark specification, are shown in Table C1 in Appendix C. In this regard the estimated coefficients on our control variables indicated that a change in the share of children in the household over time significantly reduced consumption expenditure per capita, as would be expected since they tend to consume less. With regard to the climatic variables, only rainfall significantly reduced consumption. This may be capturing the impact of floods which are a relatively frequent occurrence in Jamaica; see Burgess *et al.* (2014). Note also that not including the full set of time varying controls does not change our estimates on the hurricane indices noticeably, as shown in the last column of Table C1.

III.C Robustness Checks and Functional Form

We conduct a number of robustness checks. Firstly, since after controlling for fixed effects, hurricane shocks from the perspective of the household are arguably just random unanticipated realizations of their distribution. If we thus were to artificially reassign hurricane shocks to a year before they occurred then they should have no effect. This means essentially assigning the destruction indices from time t to time $t+1$ in equation (2). As can be seen in the last column of Table 3 one indeed finds no significant impact. We next took our data and systematically discarded the relevant sample for each storm, i.e., those observations of households during the month or up to 11 months after the storm, and re-estimated the specification of Column 4 of Table 3. The results shown in Table C2 in

[22] As with our index at time t, these are constructed by considering hurricanes within 12-24 and 24-36 months for $t-1$ and $t-2$, respectively. For those households where we do not have a survey within these lagged periods, we assume that they were located in the same building and construct the index accordingly.

Appendix C indicate that for *H_WEAK* this only marginally changes the size of the coefficient, which at all times remains negative and significant. In contrast, the coefficient on *H_STRONG* remains insignificant for all `leave out a storm' samples. This provides evidence that our results are not driven by any particular storm.

We also conducted a Fisher type randomization test where we randomly re-allocated years to households a thousand times, allowing us to compute the probability of observing our significant estimates compared to randomly assigning years. Histograms of the t-statistics from the coefficients of *H_WEAK* and *H_STRONG* shown in panels (a) and (b) of Figure C1 in Appendix C suggest that the results from Column 4 of Table 3 are unlikely due to chance. As a matter of fact, the corresponding p-value for the former was 0.04 and that of the latter 0.26. In a similar manner, we next randomized *H_WEAK* and *H_STRONG* across enumeration districts and years, and depict the corresponding histograms of the t-statistics in panels (a) and (b) of Figure C2 in Appendix C. Again these strongly suggest that our results are unlikely due to chance where the p-value was 0.022 for *H_WEAK* and 0.1 for *H_STRONG*.

The standard errors thus far are calculated assuming that on average treatment is spatially correlated according to the average extent of storm damage across enumeration districts, i.e., 60km, as noted earlier. To verify that this spatial dependence choice is not driving the significance of our estimated coefficients we experimented with a number of other thresholds, namely 10, 30, 100, and 200 km. As the results in Table C3 in Appendix 3 show, this makes little difference however.

While the functional form of our hurricane damage index is based on the physical characteristics of the storm and its energy dissipation, it is nevertheless insightful to compare results using other treatment definitions. We first took the output from our wind field model for each storm, and rather than cubing and summing it over duration of exposure, we simply included the maximum wind speed experienced in the district (*WINDMAX_WEAK* and *WINDMAX_STRONG*), thus imposing a linear relationship independent of the duration of the storm. The results of this exercise are shown in the first two columns of Table 4. Accordingly, the coefficients for weak and strong walled households are still negative, but both insignificant, suggesting considerable measurement error when damage is modelled in this more simplistic way.

We next created dummies for the terciles of the distribution of *H_WEAK* and *H_STRONG*, which essentially models damage as a spline function between these points. The results, shown in the second column of Table 4, demonstrate that for weak walled households only the middle and end part of the distribution damage values have a significant impact. In contrast, there is no significant impact for any of the three splines of *H_STRONG*.

We also tried to conduct something more akin to a traditional Difference-in-Differences (DID) analysis. More specifically, we as in Currie and Rossin-Slater (2013) defined treatment groups as those that were located within 30km of the eye of storms. Again, we allowed for heterogeneous effects by multiplying the treatment dummy by our two wall types. We first show the results of including these two dummies (*DID_WEAK* and *DID_STRONG*) and time dummies, i.e., no household or other fixed effects, in column three of Table 4. As can be seen, this indicates a negative non-significant treatment effect for weak walled and a positive significant impact for strong walled households. However, once we include regional (parish) and time effects, shown in the subsequent column, there is no longer any impact for strong walled households, but the negative impact on weak walled households doubles in size and becomes statistically significant. Including a full set of household fixed effects, as depicted in the last column, still produces a negative and significant impact for weak walled households, although the coefficient falls by 40 per cent. For households residing in buildings with strong walls the estimated impacted is still insignificant, but reverses signs. Thus taking account of household fixed effects is clearly important in trying to identify the causal effect of hurricanes on household consumption.

Finally, we experimented with lowering the minimum threshold of damage from 119 km/hr to 92 km/hr, i.e., the minimum level at which wind damage is likely to occur (see Emmanuel, 2011). The coefficients on this lower threshold damage index interacted with the two wall type dummies (*TS_WEAK* and *TS_STRONG*) are shown the last column of Table 4. Accordingly, choosing what is arguably too low of a threshold produces insignificant coefficients.

III.D Consumption Decomposition

As noted in the introduction, households may react to negative shocks, such as natural disasters, by reallocating funds away from less to more necessary consumption goods. We re-ran the specification of Column 4 Table 3 for each of our three broad consumption good groups, the estimates of which are shown in Table 5.[23] Accordingly, while the coefficient on *H_STRONG* is insignificant, possibly again due to a lack of power, *H_WEAK* has a significant negative effect in the food goods specification, indicating that in the face of hurricane damages households with weakly resistant walls reduce their consumption expenditure on food. The size of the coefficient is slightly smaller than that on total consumption, and suggests that the average damage due to a hurricane causes food consumption to fall by 1.0 per cent, whereas the largest observed damage would induce a 14.3 per cent drop. Allowing for lagged impacts, in the second column, does not suggest that the reduction in food consumption lasts beyond a year.

[23] For food and non-food consumption only 5 and 65 observations were zero, while for non-regular consumption 23 per cent were zero. We added the value of 0.01 to these so as to keep our sample size consistent across specifications when we logged the dependent variables.

There appears to be no significant, or at least not precisely estimated, reduction effect for non-food consumption when a hurricane strikes, contemporaneously or within a year; see columns three and four of Table 5. One reason may be that non-consumption goods in our case is a fairly heterogeneous basket, where, for instance, the expenditure for some goods, like clothing, is likely to decrease, but others, like construction material, may increase in response to the damages of a tropical cyclone. In contrast, like food consumption, the purchase of non-regular consumption goods decreases for both household wall type groups, as depicted in the fifth column.[24] Moreover, for the weak walled group the coefficient is multiple times larger than that on the food consumption specification, suggesting that these households strongly substitute away from non-regular consumption goods in meeting the costs due to hurricanes. As a matter of fact, our estimated coefficient suggests that the average hurricane over our sample period reduced weak walled household's non-regular consumption by 7.6 per cent, while the largest incidence decreased it by 112.5 per cent. For strong walled households, the impact on non-regular consumption is slightly higher, standing at 8.8 per cent and 129.1 per cent, for the average and maximum observed damage. We also experimented with including lags in the non-regular consumption specification in the final column. While this does not change the conclusion regarding the impact on households that reside in less wind resistant building, it does seem to suggest that there may also be a large positive effect for households in buildings with wind resistant walls a year after the event. A possible reason is that richer households with stronger walls are smoothing consumption of non-regular items and purchasing them the year after the storm by meaningful amounts. Moreover, this counter-cyclical effect seems to be serially correlated enough to be biasing our estimate. This may not be surprising since many of the storms were clustered within 2 year periods, as can be seen from the storm years listed in Table 1.

[24] One should note that dropping the zero value observations did not change our results qualitatively, although it did reduce them somewhat quantitatively for *H_STRONG*.

In comparison, Antilla-Hughes and Hsiang (2012) find negative impacts for food and items that would in our case be classified as non-regular, such as recreation and special events, but also, for goods that would be included in our non-food group, such as clothing, fuel, education, and personal care. Comparing coefficients across the larger array of their goods seems to indicate that food, at least as an aggregate group, is less responsive to tropical cyclone damage than the other goods for which a reduction in consumption expenditure is observed. This is in line with our results if one compares food to non-regular consumption. However, their implied impact is about 5 per cent compared to our 1 per cent, and thus multiple times larger. In contrast, Baez *et al.* (2015) discover an impact of about 10 per cent reduction in food consumption for the severe storm in Guatemala, compared to the implied 4.9 per cent drop for the largest value of the damage index for our data.

III.E Buffer Mechanisms

Another form of dealing with negative shocks such as tropical cyclone destruction may be to use informal forms of insurance. In this regard, one may want to note that in Jamaica a major channel of financial flows for households are remittances. In fact, remittances constitute on average 14 per cent of GDP.[25] Remittances are typically seen as a factor affecting consumption or a way to alleviate poverty in developing countries (see Acosta *et al.*, 2007; Gupta *et al.*, 2009; and Lubambu, 2014). Indeed, there is some evidence that in Jamaica remittances may act as important buffers for negative shocks (see Clarke and Wallsten, 2003; and Beuermann *et al.*, 2014). While we do not have information on the actual amount of remittances received, as noted earlier, the JSLC does indicate whether households receive remittances or not. To investigate their role in possibly buffering the shock to consumption induced by hurricanes we re-ran our benchmark specification for total consumption per capita as well as for each of its three components, also including the variable itself as well as its

[25] Authors' own calculation using World Bank data.

interaction term with *H_WEAK* and *H_STRONG*.[26] The results of this in Table C4 in Appendix C show that that neither remittances (at t-1 values) nor its interaction with the two hurricane indices are significant determinants of total per capita consumption. In contrast, the positive and significant interaction term on *H_STRONG* and Remittances indicates that remittances can serve to reduce the negative effect of hurricane damages on non-regular consumption for strong walled households. The size of the coefficient suggests that remittances can reduce the effect on non-regular consumption for the average hurricane damage to about 4.5 per cent[27], whereas for households that do not receive remittances the impact at the mean would be 12.3 per cent. When we introduce lags for both types of households the standard errors of the contemporaneous effects increase, while there is a lagged positive effect on non-regular consumption for strong walled households, further enhanced by remittances. This may again be because many of the storms over our sample came within short temporal clusters, as noted above.

Households may also draw on their savings to buffer reduction in consumption expenditure. While we do not have a direct measure of savings, the JSLC does provide us with information on whether a household receives interest payments and we take this as an indicator of having access to savings. The results of interacting the hurricane destruction index with a dummy variable for the receipt of interest payment (at t-1 values) in Table C5 in Appendix C suggest that savings can act as an efficient mechanism to buffer hurricane damage shocks for total consumption for weak walled households. As a matter of fact, if we take the estimated coefficients at face value then it can more than compensate for any overall potential reduction in consumption expenditure. However, in examining the effect of savings

[26] One may want to note that one problem is that the incidence of remittances itself may be affected by hurricane shocks, and thus its inclusion could constitute what Angrist and Pischke (2009) term a `bad control'. However, in a fixed effects logit model of remittances receipt on the positive incidence of our two hurricane indices, as well as all our other controls, hurricane destruction was not a significant predictor of remittances either at time t or lagged at time t-1.

[27] An F-test revealed that the sum of the coefficients was statistically different from zero (F = 6.01; p value = 0.0025).

on the three consumption goods it is apparent that there are some heterogeneous dynamics underlying this overall result, in that it induces households not to reduce their food consumption but rather to increase their non-food consumption. As a matter of fact, an average damaging hurricane causes a weak walled household to increase expenditure on non-food goods by 4.8 per cent. This may be because they need to buy material to deal with the repairs of damage done by the hurricane. For strong walled households we find that receiving interest payments actually substantially reinforces the negative impact of hurricane damages.

Section IV: Sample Selection Bias

There are a number of potential sample selection bias issues with regard to our use of the Jamaican data that merit further scrutiny. Firstly, one worry is that our constructed panel is not representative of all households surveyed in the JSLC, particularly with regard to hurricane wind exposure. To investigate this, we calculated *H_WEAK* and *H_STRONG* for all households not in our panel sample, pooled the two samples[28], and then ran a linear probit model (allowing for spatial correlation) of whether the incidence of non-zero damages can predict inclusion in the sample, including our other controls. However, the coefficients were insignificant.[29]

A related concern is that even within our restricted panel not all households that should have been would have been re-surveyed in subsequent years. One reason for this could be that households most affected by the storms may have migrated[30] or substantially changed composition so that they would not be matched via Handa's (2008) matching procedure. To

[28] The mean for the strong and weak incidence dummy was 0.08 and 0.18, respectively.

[29] The coefficient on *H_WEAK* was 0.032 and its standard error 0.047, while that on *H_STRONG* was 0.053 with a standard error of 0.045.

[30] The disaster-migration literature demonstrates that natural disasters can positively impact the movement of people outside of their countries of origin (including Reuveny and Moore, 2009; Drabo and Myabe, 2015). This view is also evident in the Central America and Caribbean region, where the average hurricane increases migration by about 6% (Spencer and Urquhart 2018).

gain some insight into whether this might potentially be a problem, we created an indicator variable of whether a household drops out of a panel even though it potentially could have been resurveyed. We then ran a linear probit model (allowing for spatial correlation) on whether a non-zero *H* can predict dropout for weak and strong walled households, including our other controls. Again, hurricane destruction was not a significant predictor for either.[31]

Finally, household composition may change as a result of hurricane damages.[32] We utilize data from the JSLC that reports whether individuals are still or no longer members since the last survey and if there are any new members. These information allow us to construct the proportion of household members that are no longer members, and we regressed the two hurricane destruction indices on this share to see whether there is any evidence of this change in household composition due to hurricane strikes. But the insignificant coefficients on *H_STRONG* and *H_WEAK* did not suggest that migration was induced by hurricane destruction.[33]

Section V: Conclusion

This paper investigated the impact of hurricane strikes on household consumption in Jamaica. To achieve this we constructed a panel of households and measures of their consumption and linked this to an index of hurricane damages that takes into account the detailed physical characteristics of the storm and the location of the household relative to the storm. In congruence with most of the literature we find that household consumption are negatively impacted by tropical cyclones, and that this effect is only short-term. Moreover, while the average storm will not reduce household consumption too much, large storms can

[31] Coefficients (standard errors) were -0.015 (0.038) and -0.030 (0.034) for *H_WEAK* and *H_STRONG*, respectively.

[32] As noted by Currie and Rossin-Slater (2013), endogenous migration is likely to be a problem in many studies on hurricanes.

[33] Coefficients (standard errors) were 0.001 (0.005) and 0.002 (0.012) for *H_WEAK* and *H_STRONG*, respectively.

have a considerable impact. Importantly, our econometric results demonstrate that not controlling for household time invariant unobservables, as for instance in only having access to cross-sectional data, may bias any negative impact downward. We also investigate whether there is a different treatment effect on households depending on whether they reside in hurricane wind resistant versus less resistant building types. This is indeed the case, where total consumption per capita is only impacted in households in buildings with weaker walls.

We explored whether households, in the absence of formal insurance mechanisms, buffer the negative effects of hurricanes in Jamaica. Firstly, subsequent to these storms, there is considerable reallocation of a household's budget across goods. More specifically, households in weakly wind resistant walled buildings reduce non-regular consumption substantially more than expenditure on food, suggesting that they reallocate their budget towards necessities after a negative shock. In contrast, although there was no apparent change in total consumption, there is some evidence that households in less vulnerable housing also reduce their non-regular consumption. Further inquiries into possible informal financial buffers suggest that these also play a role. In particular, households in more wind resistant buildings possibly buffer the loss in non-regular consumption by receipt of remittances. In contrast, households living in buildings that are more susceptible to hurricane damage appear to use savings to increase their non-food consumption, possibly due to higher expenditure to accommodate repairs.

More generally, our results suggest that households in developing countries can be vulnerable to hurricane shocks at least in the short-term, and if they live in less wind damage resistant buildings. However, they do have some buffering mechanisms in place, in the form of other financial flows and reallocation of their spending across goods, in order to deal with these shocks. Thus, any assessment of the need for more formal tropical cyclone damage insurance should take current existing buffering practices into account. Finally, one should note that our analysis is restricted to examining only one aspect of the impact, namely household consumption. There are of course other aspects of households that may be impacted which will not be easily picked up by consumption patterns, such as birth outcomes, and children's education and health, where these may have a much more long lasting effect.[34] This could be a fruitful direction of future research in the Jamaican context.

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[34] See, for instance, Salas (2015), de Oliveira and Quintana-Domeque (2016),Triyana and Xia (2017), Karbownik and Wray (2016), Deuchert and Felfe (2016), and Caruso (2017).

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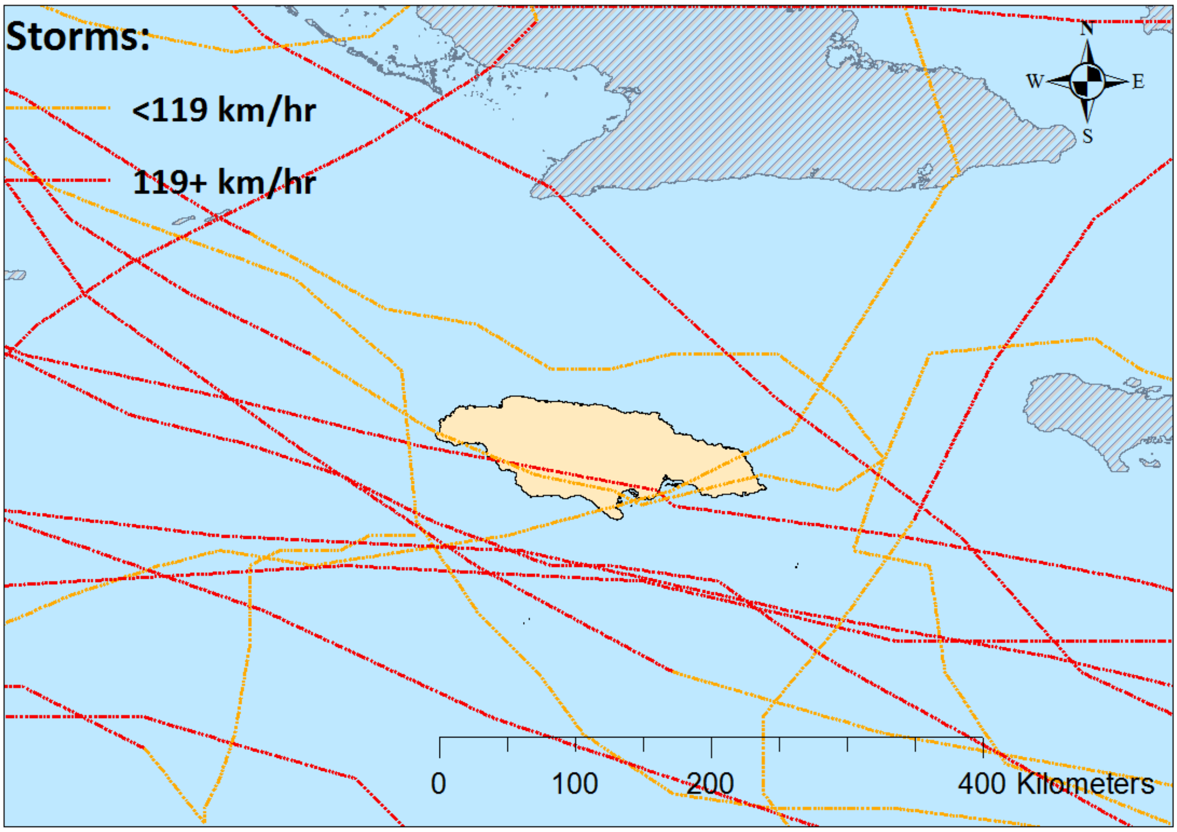
Figures and Tables

Figure 1: Hurricanes Affecting Jamaica over 1988-2010



Note: The red portion of the line indicates when the storm was classified as a hurricane (minimum maximum wind speed of 119 km/hr) and as a tropical storm otherwise.

Table 1: Damaging Storms: 1990-2010

STORM	YEAR (MONTH)	Saffir-Simpson	Parish Most Affected	Landfall (as Hurricane)
GILBERT	1988 (September)	5	St. Andrew	Yes
GORDON	1994 (November)	1	St. Mary	No
MITCH	1998 (October)	5	Westmoreland	No
IRIS	2001 (November)	4	Clarendon	No
ISIDORE	2002 (September)	3	Westmoreland	No
LILI	2002 (September)	3	Hannover	No
CHARLEY	2004 (August)	3	Westmoreland	No
IVAN	2004 (September)	5	Clarendon	No
DENNIS	2005 (July)	3	Portland	No
EMILY	2005 (July)	5	Westmoreland	No
WILMA	2005 (November)	5	Westmoreland	No
DEAN	2007 (August)	5	St. Elizabeth	No
GUSTAV	2008 (August)	4	Portland	No
IKE	2008 (September)	3	St. Mary	No
PALOMA	2008 (November)	3	Hannover	No
TOMAS	2010 (November)	1	St. Thomas	No

Table 2 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Expenditure per capita variables				
Consumption per capita	15776.97	17372.63	90.45	1452460
Share of consumption:				
Food	0.61	0.18	0	1
Non-food	0.36	0.18	0	1
Non-regular	0.03	0.14	0	1
Share of children	0.26	0.27	0	1
Remittances	0.55	0.49	0	1
Interest	0.05	0.21	0	1
H/1.0e+09 (>0)	0.37	1.20	0.0001	8.33
H_WEAK	0.63	1.62	0.0002	8.33
H_STRONG	0.54	0.99	0.0001	4.00
WINDMAX_WEAK	176.2	54.4	119.1	347.9
WINDMAX_STRONG	194.1	61.7	119.0	359.0
SSS1_2_WEAK	0.05	0.22	0	1
SSS1_2_STRONG	0.12	0.32	0	1
SSS3_+_WEAK	0.03	0.17	0	1
SSS3_+_STRONG	0.11	0.32	0	1
DID_WEAK	0.06	0.24	0	1
DID_STRONG	0.10	0.30	0	1

Table 3: Regression Results - Total Consumption

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
H_t	-0.001	-0.004	-0.019*				
	(0.014)	(0.012)	(0.008)				
H_WEAK_t				-0.019*	-0.021*	-0.020*	
				(0.008)	(0.010)	(0.010)	
H_STRONG_t				-0.010	-0.016	-0.013	
				(0.017)	(0.022)	(0.022)	
H_WEAK_{t-1}					-0.006	-0.006	
					(0.012)	(0.012)	
H_STRONG_{t-1}					-0.012	-0.012	
					(0.028)	(0.027)	
H_WEAK_{t-2}						-0.050	
						(0.242)	
H_STRONG_{t-2}						0.355	
						(0.358)	
H_WEAK_{t+1}							0.020
							(0.011)
H_STRONG_{t+1}							0.001
							(0.002)
Model:	OLS	OLS	HH FE	HH FE	HH FE	HH FE	HH FE
Controls:	No	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dep.:	60km	60km	60km	60km	60km	60km	60km
Obs.:	23,611	23,611	23,611	23,611	23,611	23,611	23,611
Nr. of HHs:	9,546	9,546	9,546	9,546	9,546	9,546	9,546

Notes: (i) Time (Month-Year) dummies included; (ii) ** and * are 1 and 5 per cent significance levels respectively; (iii) Spatial dependence corrected standard errors are in parentheses.

Table 4: Functional Form

Model:	(1)	(2)	(3)	(4)	(5)	(6)
$WINDMAX\_WEAK_t$	-0.0003					
	(0.0003)					
$WINDMAX\_STRONG_t$	-0.0001					
	(0.0003)					
$H\_WEAK(1^{st}\ tercile)_t$		12.027				
		(7.594)				
$H\_WEAK(2^{nd}\ tercile)_t$		-1.320*				
		(0.585)				
$H\_WEAK(3^{rd}\ tercile)_t$		-0.021**				
		(0.007)				
$H\_STRONG(1^{st}\ tercile)_t$		-3.041				
		(22.258)				
$H\_STRONG(2^{nd}\ tercile)_t$		-0.272				
		(2.044)				
$H\_STRONG(3^{rd}\ tercile)_t$		-0.009				
		(0.017)				
DID_WEAK_t			-0.069	-0.151**	-0.079*	
			(0.041)	(0.049)	(0.037)	
DID_STRONG_t			0.137*	0.030	-0.067	
			(0.039)	(0.049)	(0.036)	
TS_WEAK						-0.041
						(0.021)
TS_STRONG						-0.002
						(0.017)
Model:	HH FE	HH FE	OLS	RE FE	HH FE	HH FE
Controls:	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dependence:	60km	60km	60km	60km	60km	60km

Notes: (i) Time (Month-Year) dummies included; (ii) ** and * are 1 and 5 per cent significance levels respectively; (iii) Spatial dependence corrected standard errors are in parentheses; (iv) Sample size is 23,611.

Table 5: Regression results – Consumption Components

Model:	(1)	(2)	(3)	(4)	(5)	(6)
H_WEAK_t	-0.017**	-0.018	-0.012	-0.014	-0.135**	-0.111*
	(0.006)	(0.009)	(0.011)	(0.014)	(0.043)	(0.048)
H_STRONG_t	-0.021	-0.027	-0.002	-0.009	-0.155*	-0.036
	(0.016)	(0.024)	(0.024)	(0.029)	(0.066)	(0.075)
H_WEAK_{t-1}		-0.001		-0.010		0.037
		(0.012)		(0.017)		(0.045)
H_STRONG_{t-1}		-0.013		-0.017		0.242*
		(0.028)		(0.038)		(0.079)
Dep. Var:	Food	Food	Non-Food	Non-Food	Non-Regular	Non-Regular
Model:	HH FE	HH FE	HH FE	HH FE	HH FE	HH FE
Controls:	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dependence:	60km	60km	60km	60km	60km	60km

Notes: (i) Time (Month-Year) dummies included; (ii) ** and * are 1 and 5 per cent significance levels respectively; (iii) Spatial dependence corrected standard errors are in parentheses; (iv) Sample size is 23,611.

Appendix A: Wind Field Model

We use Boose *et al.*'s (2004) version of the well-known Holland (1980) wind field model. More specifically, the wind experienced at time t due to hurricane k at any point $P=j$, i.e., W_{jk} is given by:

$$W_{j,k,t} = GF\left[V_{m,k,t} - S\left(1-\sin\left(T_{i,k,t}\right)\right)\frac{V_{h,k,t}}{2}\right]\left[\left(\frac{R_{m,k,t}}{R_{i,k,t}}\right)^{B_{jt}} \exp\left(1-\left[\frac{R_{m,k,t}}{R_{i,k,t}}\right]^{B_{jt}}\right)\right]^{\frac{1}{2}} \qquad \text{(A1)}$$

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 pixel of interest, $P=j$, 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. The remaining ingredients in (A1) consist of the gust factor G and the scaling parameters F, S, and B, for surface friction, asymmetry due to the forward motion of the storm, and the shape of the wind profile curve, respectively.

In terms of implementing (A1), one should note that V_m is given by the storm track data described in the data section, V_h can be directly calculated by following the storm's movements between locations along its track, and R and T are calculated relative to the point of interest $P=j$. All other parameters have to be estimated or assumed. For instance, we have no information on the gust wind factor G, but a number of studies (e.g., Paulsen and Schroeder, 2005) have measured G to be around 1.5, and we also use this value. For S we follow Boose *et al*. (2004) and assume it to be 1. While we also do not know the surface friction to directly determine F, Vickery *et al*. (2009) note that in open water the reduction factor is about 0.7 and reduces by 14% on the coast and 28% further 50 km inland. We thus adopt a reduction factor that linearly decreases within this range as we consider points *i* further inland from the coast. To determine *B* we employ Holland's (2008) approximation method, whereas we use the parametric model estimated by Xiao *et al*. (2009) to estimate R_{max}. Our source for hurricane track data is the HURDAT Best Track Data, which provides six hourly data on all tropical cyclones in the North Atlantic Basin, including the position of the eye and the maximum wind speed of the storm. These tracks are linearly interpolated to hourly positions. Finally, as set of points, $j=1,\ldots J$ we take the centroid of the enumeration districts in Jamaica.

Appendix B: Additional Statistics

Figure B1: Enumeration Districts in Jamaica

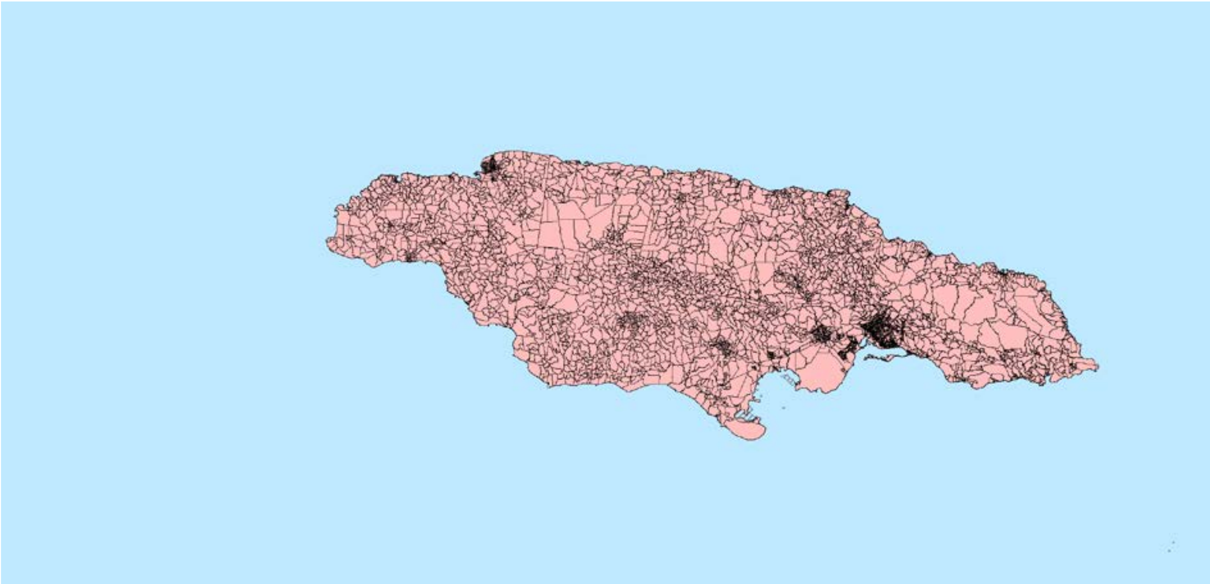
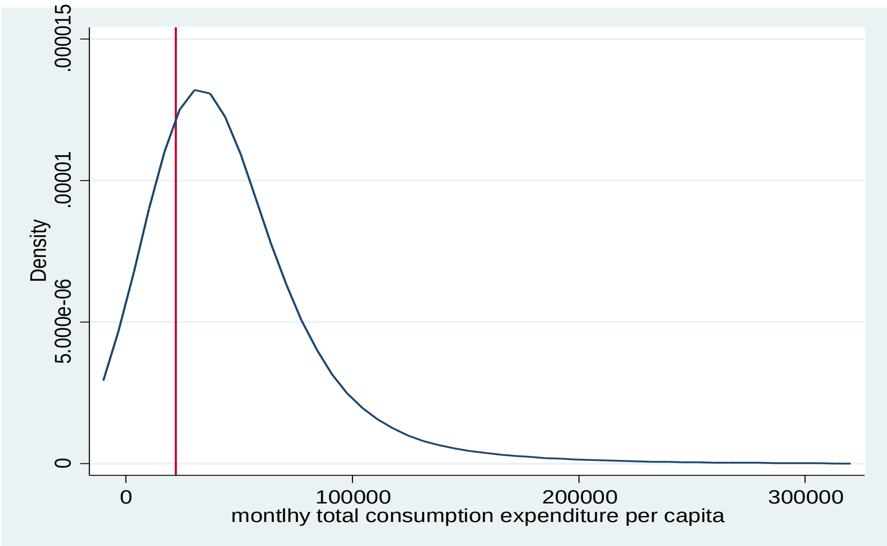


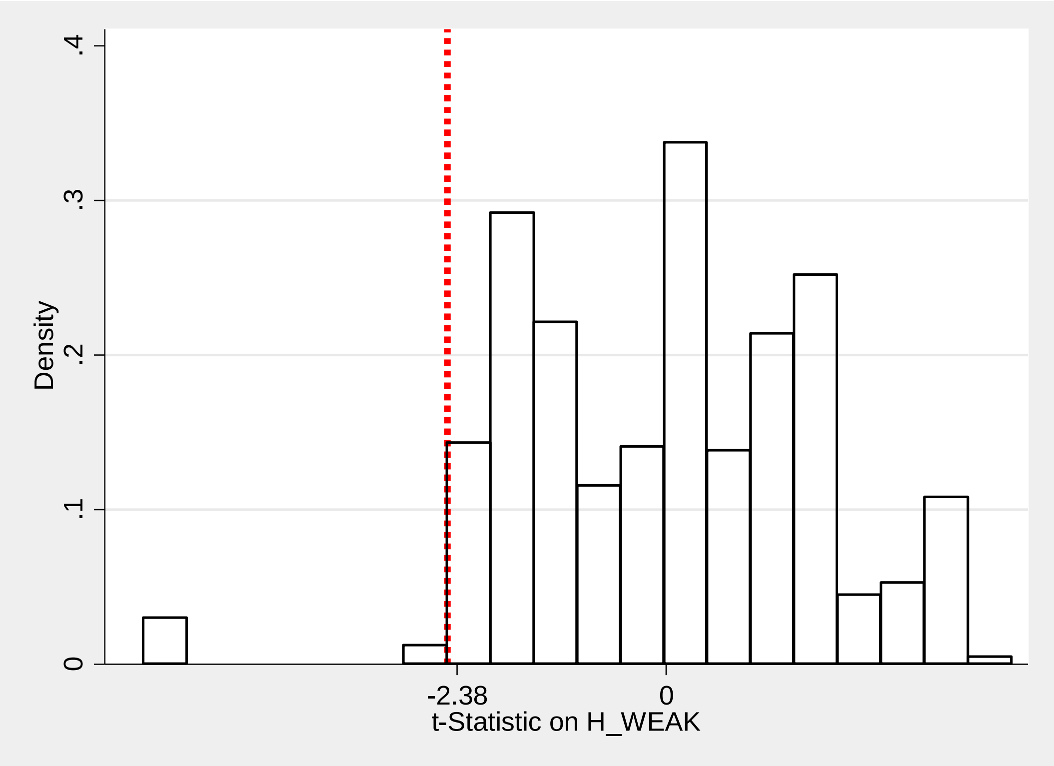
Figure B2: Distribution of Consumption Expenditure Per Capita

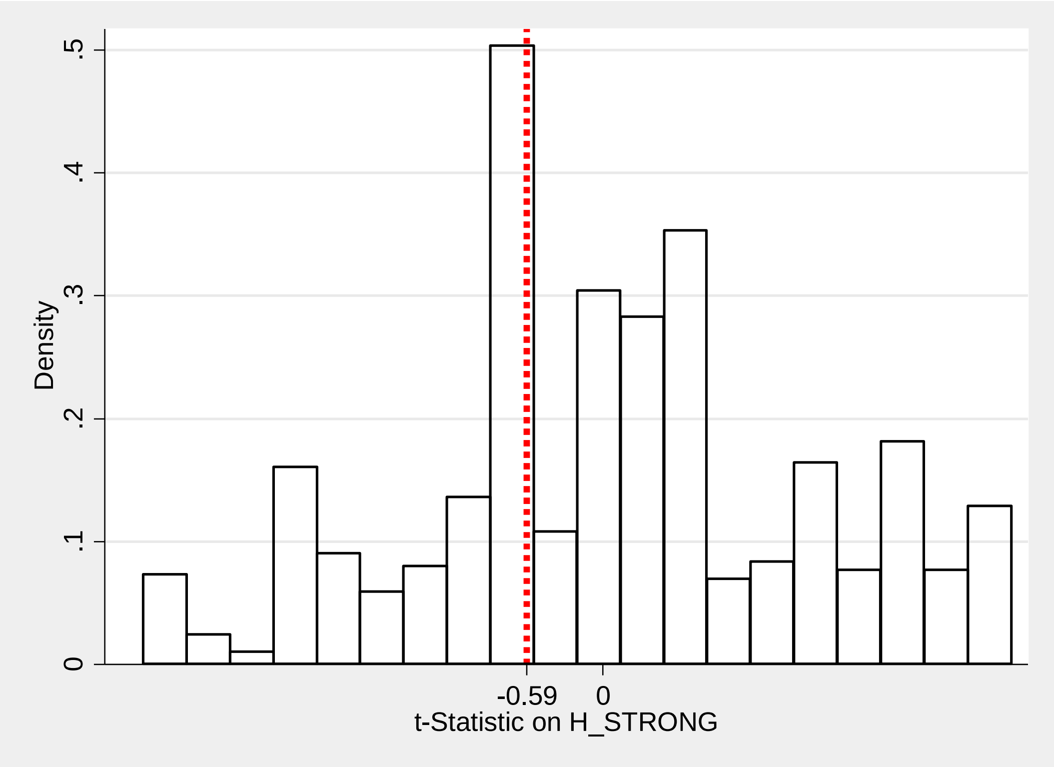


Notes: (i) Graph of kernel density distribution using a Gaussian kernel and a plug-in bandwidth; (ii) The red line is the consumption-based poverty threshold of J$21,895 using data from the Survey of Living Conditions (PIOJ, 2011).

Appendix C: Additional Robustness Checks

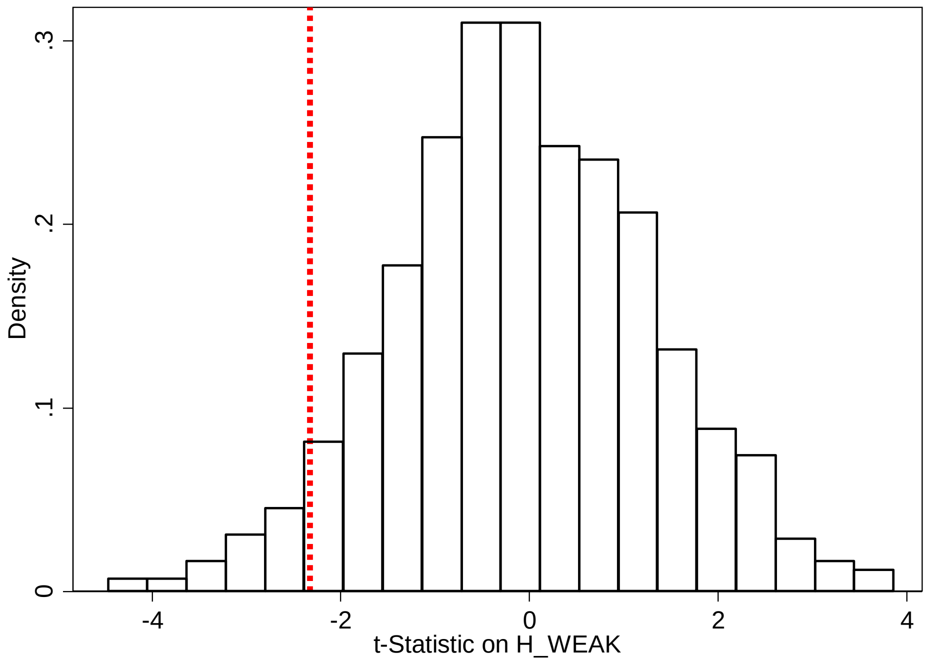
Figure C1: Histograms of T-Statistics of Randomization Tests of "Leave One Storm Out'





Notes: (i) Red vertical lines indicate estimated t-statistic from non-randomized regressions.

Figure C2: Histograms of T-Statistics of Randomization Tests of Randomly assigned Damage across Space and Time



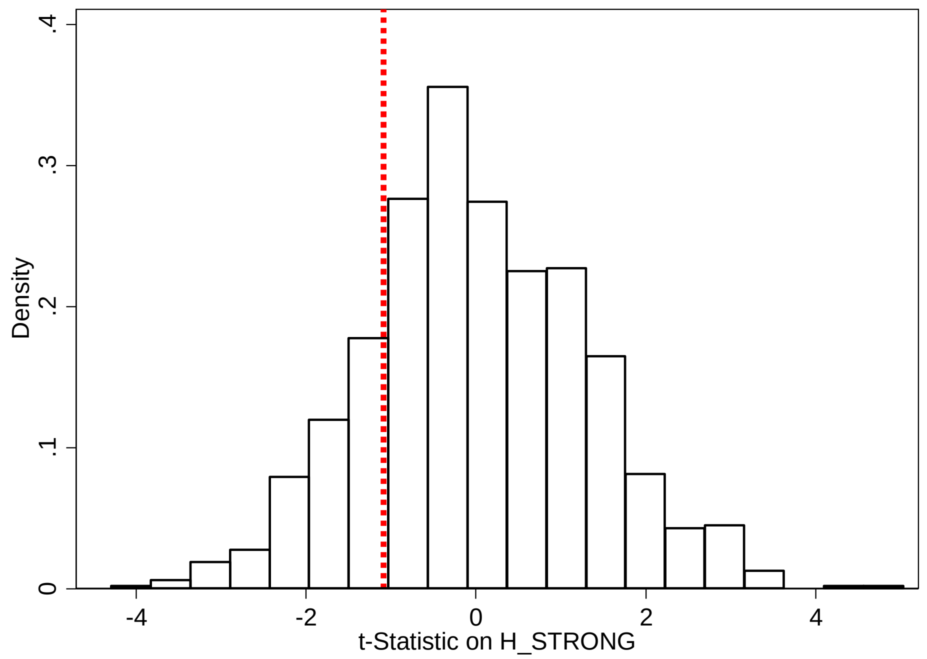


Table C1: Full Regression Results – Benchmark Specification (with and time varying without controls)

Model:	(1)	(2)
H_WEAK_t	-0.019*	-0.018*
	(0.008)	(0.008)
H_STRONG_t	-0.010	-0.007
	(0.017)	(0.017)
$SHARE\_CHILD_t$	-0.444**	
	(0.040)	
$Rain_t$	-0.0004**	
	(0.0001)	
$TEMPERATURE_t$	-0.105	
	(0.0.48)	
Model:	HH FE	
Controls:	Yes	
Spatial Dependence:	60km	
Observations:	23,611	

Notes: (i) Time (Month-Year) dummies included; (ii) ** and * are 1 and 5 per cent significance levels respectively; (iii) Spatial dependence corrected standard errors are in parentheses.

Table C2: Regression Results - 'Leave Out Storm' Specifications

Omitted Storm:	β_{H_WEAK}	$Std.Error_{H\_WEAK}$	β_{H_STRONG}	$Std.Error_{H\_STRONG}$
Gordon	-0.019*	(0.008)	-0.011	(0.017)
Mitch	-0.019*	(0.008)	-0.009	(0.016)
Iris	-0.018*	(0.008)	-0.009	(0.016)
Isidore	-0.019*	(0.008)	-0.010	(0.016)
Lili	-0.019*	(0.008)	-0.010	(0.016)
Charley	-0.023*	(0.010)	-0.022	(0.021)
Ivan	-0.024*	(0.010)	-0.016	(0.020)
Dennis & Emily	-0.022*	(0.009)	-0.025	(0.019)
Wilma	-0.022*	(0.010)	-0.014	(0.021)
Dean	-0.019*	(0.008)	-0.010	(0.017)
Gustav	-0.017*	(0.007)	-0.009	(0.017)
Ike	-0.018*	(0.007)	-0.010	(0.017)
Paloma	-0.018*	(0.008)	-0.010	(0.017)
Thomas	-0.019*	(0.008)	-0.010	(0.017)
Model:	HH FE		HH FE	
Controls:	Yes		Yes	
Spatial Dep.:	60km		60km	

Notes: (i) Time (Month-Year) dummies included; (ii) ** and * are 1 and 5 per cent significance levels respectively; (iii) Spatial dependence corrected standard errors are in parentheses; (iv) Sample size is 23,611.

Table C3: Alternative Spatial Dependence

Model:	(1)	(2)	(3)	(4)
H_WEAK_t	-0.019*	-0.019*	-0.019**	-0.019*
	(0.008)	(0.008)	(0.007)	(0.008)
H_STRONG_t	-0.010	-0.010	-0.010	-0.010
	(0.017)	(0.016)	(0.014)	(0.012)
Model:	HH FE	HH FE	HH FE	HH FE
Controls:	Yes	Yes	Yes	Yes
Spatial Dependence:	10km	30km	100km	200km

Notes: (i) Time (Month-Year) dummies included; (ii) ** and * are 1 and 5 per cent significance levels respectively; (iii) Spatial dependence corrected standard errors are in parentheses; (iv) Sample size is 23,611.

Table C4: Regression Results – Role of Remittances (*Remit*)

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
H_WEAK$_t$	-0.019*	-0.022*	-0.017*	-0.018	-0.016	-0.018	-0.132*	-0.107
	(0.009)	(0.011)	(0.008)	(0.011)	(0.012)	(0.015)	(0.054)	(0.057)
H_STRONG$_t$	-0.013	-0.020	-0.026	-0.033	-0.003	-0.013	-0.216*	-0.010
	(0.017)	(0.023)	(0.016)	(0.023)	(0.027)	(0.033)	(0.067)	(0.074)
H_WEAK$_{t-1}$		-0.009		-0.003		-0.009		0.043
		(0.014)		(0.014)		(0.018)		(0.050)
H_STRONG$_{t-1}$		-0.021		-0.021		-0.025		0.254**
		(0.029)		(0.029)		(0.041)		(0.089)
H_WEAK$_t$**Remit*	0.001	0.001	0.0002	0.001	0.008	0.009	-0.002	-0.002
	(0.009)	(0.009)	(0.0134)	(0.013)	(0.012)	(0.012)	(0.060)	(0.060)
H_STRONG$_t$**Remit*	0.006	0.008	0.010	0.012	0.004	0.007	0.137*	0.138*
	(0.009)	(0.010)	(0.011)	(0.011)	(0.019)	(0.019)	(0.067)	(0.067)
H_WEAK$_{t-1}$**Remit*		0.005		0.005		-0.0004		-0.013
		(0.009)		(0.009)		(0.0141)		(0.046)
H_STRONG$_t$**Remit*		0.018		0.016		0.016		-0.026
		(0.010)		(0.011)		(0.020)		(0.066)
Remit	0.004	0.002	0.008	0.006		0.004	0.014	0.017
	(0.007)	(0.007)	(0.006)	(0.007)	()	(0.013)	(0.030)	(0.030)
Dep. Var:	Total	Total	Food	Food	Non-Food	Non-Food	Non-Regular	Non-Regular
Model:	HH FE	HH FE	HH FE	HH FE	HH FE	HH FE	HH FE	HH FE
Controls:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dependence:	60km	60km	60km	60km	60km	60km	60km	60km

Notes: (i) Time (Month-Year) dummies included; (ii) ** and * are 1 and 5 per cent significance levels respectively; (iii) Spatial dependence corrected standard errors are in parentheses; (iv) Sample size is 23,611.

Table C5: Regression Results – Role of Interest Receipt (*Int*)

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
H_WEAK_t	-0.021**	-0.024*	-0.02**	-0.018	-0.015	-0.018	-0.137**	-0.111*
	(0.008)	(0.010)	(0.006)	(0.009)	(0.011)	(0.014)	(0.043)	(0.045)
H_STRONG_t	-0.008	-0.014	-0.021	-0.027	0.001	-0.005	-0.137*	-0.019
	(0.017)	(0.021)	(0.016)	(0.024)	(0.024)	(0.029)	(0.068)	(0.076)
H_WEAK_{t-1}		-0.006		-0.001		-0.009		0.031
		(0.012)		(0.012)		(0.017)		(0.045)
H_STRONG_{t-1}		-0.010		-0.012		-0.011		0.218**
		(0.027)		(0.028)		(0.037)		(0.082)
H_WEAK_t*Int	0.058**	0.058**	0.011	0.011	0.085**	0.085*	0.006	0.027
	(0.020)	(0.020)	(0.015)	(0.015)	(0.030)	(0.030)	(0.187)	(0.187)
H_STRONG_t*Int	-0.019	-0.019	-0.001	-0.001	-0.038	-0.040	-0.446**	-0.435*
	(0.027)	(0.028)	(0.022)	(0.023)	(0.049)	(0.049)	(0.105)	(0.107)
$H\_WEAK_{t-1}*Int$		0.0122		0.006		0.018		0.183
		(0.018)		(0.016)		(0.030)		(0.202)
$H\_STRONG_{t-1}*Int$		-0.020		-0.002		-0.044		0.339*
		(0.023)		(0.026)		(0.041)		(0.147)
Int	-0.001	-0.00001	0.013	0.013	-0.002	0.001	-0.073	-0.126
	(0.017)	(0.01807)	(0.018)	(0.019)	(0.027)	(0.028)	(0.075)	(0.077)
Dep. Var:	Total	Total	Food	Food	Non-Food	Non-Food	Non-Regular	Non-Regular
Model:	HH FE	HH FE	HH FE	HH FE	HH FE	HH FE	HH FE	HH FE
Controls:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dep:	60km	60km	60km	60km	60km	60km	60km	60km

Notes: (i) Time (Month-Year) dummies included; (ii) ** and * are 1 and 5 per cent significance levels respectively; (iii) Spatial dependence corrected standard errors are in parentheses; (iv) Sample size is 23,611.