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ABSTRACT

Gone with the Storm: Rainfall Shocks and Household Well-Being in Guatemala*

This paper investigates the causal consequences of Tropical Storm Agatha (2010) – the strongest tropical storm ever to strike Guatemala since rainfall records have been kept – on household welfare. The analysis reveals substantial negative effects, particularly among urban households. Per capita consumption fell by 12.6%, raising poverty by 5.5 percentage points (an increase of 18%). The negative effects of the shock span other areas of human welfare. Households cut back on food consumption (10% or 43 to 108 fewer calories per person per day) and reduced expenditures on basic durables. These effects are related to a drop in income per capita (10%), mostly among salaried workers. Adults coped with the shock by increasing their labor supply (on the intensive margin) and simultaneously relying on the labor supply of their children and withdrawing them from school. Impact heterogeneity is associated with the intensity of the shock, food price inflation, and the timing of Agatha with respect to the harvest cycle of the main crops. The results are robust to placebo treatments, household migration, issues of measurement error, and different samples. The negative effects of the storm partly explain the increase in poverty seen in urban Guatemala between 2006 and 2011, which national authorities and analysts previously attributed solely to the collateral effects of the global financial crisis.

JEL Classification: I3, J2, O1

Keywords: economic development, natural disasters, consumption, poverty, human capital

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1. Introduction

Climate is often referred to as an important determinant of economic performance. More recently, largely motivated by the ongoing debate on global warming, the influence of climate factors on economically relevant outcomes has attracted even more attention. With temperatures expected to continue rising and scientists projecting an increase in the frequency and severity of extreme weather events, understanding the consequences of weather-related shocks on economic development, particularly on human welfare, is increasingly important. The aggregated first-order effects of natural disasters such as human deaths and injuries, destruction of critical infrastructure, and disruption of economic activities are evident. Yet, quantifying the direct and indirect (short- and long-term) effects of large shocks on the well-being of households and assessing how they cope with these risk factors is more challenging while at the same time it is central to more fully estimating their economic impacts and designing effective risk management strategies (World Bank, 2013).

The last few years have seen a large body of empirical research that examines the effects of anomalous deviations in weather outcomes on a wide range of variables associated with household welfare as well as households' capacity to protect their welfare when confronted by such shocks. The outcome variables analyzed range from consumption to income to asset ownerships to mortality to investments in education, health and nutrition to risk-coping actions, among others (See Dell et al. 2013 and Baez et al. 2010 for surveys of this literature). At least three clear patterns emerge from the existing literature. First, households possess numerous strategies for dealing with extreme weather but overall their mitigation capacity is insufficient for the task of maintaining –let alone improving– their welfare. For instance, excess rainfall and droughts have been found to reduce by half the crop income among affected households in Burkina Faso and more than half of this loss is directly reflected in consumption (Kazianga and Udry 2006). Similarly, rainfall shocks were found to force households in rural Ethiopia to deplete their productive assets between 8% and 62% (Dercon 2004). The second observation has to do with the persistence of the effects. There is a host of empirical results indicating that the immediate negative consequences of weather shocks often carry over the longer term. Alderman et al. (2006) show, for instance, that children who became stunted due to a drought in Zimbabwe never fully recovered later in life and exhibited lower school attainment and earnings in adulthood. Finally, there is remarkable impact heterogeneity. The evidence consistently shows that the poorer populations often carry the heaviest burden. For example, stunting in children after the floods that hit Bangladesh in 1998 was substantially higher among households in the bottom 40 percentile of the consumption distribution (Del Ninno and Lundberg 2005).

Seeking to contribute to that literature, this paper looks at the vulnerability of households to large rainfall shocks in a context where natural risks are prevalent and poverty is pervasive, with more than half of the population living in poverty. More specifically, employing a double-difference (D-D) analysis that exploits spatial and time variation in extreme (excessive) rainfall, we investigate whether households in the proximity of Agatha –a major tropical storm that hit Guatemala in 2010 and dropped the largest rainfall in the country since 1963– saw a fall in their consumption and were likely to fall further into poverty as result of the event, and whether they engaged in sub-optimal strategies to confront the shock. The paper also examines the variability of the impacts across different groups of people and postulates hypotheses about some of the potential mechanisms at play. The data used for this study come from two cross-sections of national representative household-level survey data collected before (2006) and almost one year after the storm occurred (2011) as well as administrative data with monthly rainfall and temperature data for the period 1963-2013 recorded by 73 meteorological stations scattered across Guatemala.

The study finds that household welfare, measured by per capita consumption, fell on average by 8.2% of the median consumption at the baseline among affected households (i.e. located in areas where the windstorm brought rainfall substantially above the historical levels) relative to households less affected or not affected by Agatha. Further inspection of the data shows, however, that the losses in consumption attributed to the shock arose mostly among households from urban areas, which experienced a decline of 12.6% of their median consumption at baseline. Point estimates from a specification that captures variation in the intensity of the shock with categorical levels of precipitation anomalies yield similar results, with the impact on per capita consumption ranging from 9% to 14%. Nearly half the drop in consumption is explained by a reduction in food expenditures of 10% that correspond to 43-108 fewer calories per person per day. Affected households also cut back expenditures on durables, including basic items such as a stoves or refrigerators.

The fall in consumption due to Agatha increased the overall poverty rate by 3 percentage points or 7%. In line with the effects on consumption, this result is driven entirely by a higher incidence of poverty in urban areas, which saw a statistically significant increase of 5.5 percentage points (18%). Roughly speaking, these effects translate into 80,000 more families falling into poverty as a result of Agatha. The negative effects of the storm partly explain the increase in poverty observed in urban Guatemala (from 30% to 35%) between 2006 and 2011, which the national authorities and analysts previously attributed solely to the collateral effects of the global financial crisis.

Unpacking the mechanisms of transmission, we find that Agatha reduced income per capita in affected areas on average by 10%, mostly among salaried workers. In an effort to cope with the shock, adults –particularly urban men– increased their labor supply (on the intensive margin) on average by almost 2.5 additional hours per week (5.3%). Similarly, the engagement of affected rural children in paid and unpaid work increased by 12.8%, which came at the cost of reducing their school participation (2.6%).

Supplementary analyses confirm the robustness of the negative effects uncovered in this paper. The results hold after performing two placebo tests, including one that uses a "fake" treatment to test the central underlying assumption of parallel trends and another one to test for the possibility of endogenous compositional changes in the treatment and comparison groups over time. The results are also very robust to other issues such as migration, the overlap of Agatha with other precipitation anomalies, and different definitions of the shock using varying critical thresholds.

There is substantial impact heterogeneity between urban and rural areas. A leading factor is the strength of the shock itself. Our evidence shows that Agatha dropped relatively much more rainfall over urban areas. We also observe some suggestive evidence that increases in food prices accelerated after the shock in some parts of the region that saw the largest precipitation anomalies. In contrast, the relatively low sensitivity of rural households may be partly explained by the timing of Agatha with respect to the local agricultural cycles. For the most part, the excessive precipitation fell in a period of the harvesting season that was not harmful for maize, beans, coffee and sugar cane, the main crops grown in affected areas. Finally, a large

CCT program targeted mostly to rural households could have also helped protect their basic welfare in the aftermath of the shock.

The results of this paper are in line with evidence from previous studies that have investigated the vulnerability of households to natural disasters in Guatemala. In 2005, the country was hit by Stan, another tropical storm, which was found to increase child labor and reduce school participation for children aged 13 to 15 (Bustelo, 2012). Similarly, human capital formation was disrupted by a strong earthquake that struck Guatemala in 1976. An increase of a standard deviation in the intensity of the earthquake was associated with a reduction of 0.2 and 0.4 years of schooling among individuals exposed to the disaster in early childhood and school age, respectively (Hermida, 2010). Contrary to these pieces of evidence, our paper highlights that urban households carried the burden of the consequences of the shock.

The rest of the paper is structured as follows. The next section provides background information on the natural disaster and the socioeconomic context in which it took place. Section 3 describes the data used in the analysis. Section 4 describes the identification strategy. Section 5 presents the empirical results, including discussion on robustness checks and interpretation of the findings. Finally, section 6 concludes.

2. Country Context and Tropical Storm Agatha

Guatemala, a lower-middle-income country, is the third largest in terms of land area in Central America (after Nicaragua and Honduras). Poverty is pervasive across the country. As of 2006, four years before the shock examined in this paper, the per capita consumption of over half of the population (51%) was below the national poverty line. Poverty rates in rural areas have historically been on the order of 70% to 80%. The precarious socioeconomic environment is further compounded by high incidence of malnutrition and infant mortality rates and low coverage and quality of basic services such as electricity, water and sanitation.

The large risk exposure of Guatemala to natural disasters poses a serious threat to the human welfare of its population. The geographic location of the country makes it prone to frequent and high-intensity geological and weather-related shocks such as earthquakes, volcanic eruptions, droughts, storms and hurricanes. In fact, Guatemala ranks 5th worldwide based on its economic risk to natural hazards (CEPAL et al. 2011).[1] Similarly, the Global Climate Risk Index puts Guatemala in 12th place worldwide based on the number of extreme weather events recorded between 1991 and 2010 –and in 2nd place for events recorded only in 2010 (Harmeling 2011).

Tropical Storm Agatha exemplifies the high vulnerability of Guatemala to natural risks. Triggered by a tropical wave that moved westward from the coast of Africa on May 8, 2010, Agatha originated as a tropical depression on May 29, 2010 in the eastern Pacific. A few hours later the tropical depression developed into a cyclone, making landfall in Champerico, southwest of Guatemala, near the border with Mexico, at 16:40. The surface circulation of Agatha weakened as it continued northeastward into the Sierra Madre Mountains and it began to dissipate on May 30 over northwestern Guatemala.

Reaching top winds of nearly 80 kilometers/hour, Agatha produced torrential rains, widespread floods and landslides across several countries in Central America. Guatemala, however, was the hardest hit. Some parts of the country received more than 910 millimeters of rainfall, the highest levels recorded in over 60 years, making Agatha the strongest tropical cyclone to ever strike Guatemala in terms of amount of rain dropped since records have been kept. The human losses, the destruction of homes, crops and critical infrastructure –including schools and health centers– and their subsequent disruption of economic and institutional systems forced government officials to declare a state of emergency for the entire country. Assessments conducted jointly by national and international institutions estimated that nearly 400,000 people (around 3% of the total population) needed humanitarian assistance and the total damages attributed to the storm amounted to 2.2% of the GDP. Donations centers spread across the country started deploying relief aid started on May 31, but anecdotal evidence suggests that this assistance was far from sufficient to mitigate the immediate consequences of the disaster (CEPAL et al. 2011).

3. Data

Two main sources of data underlie the empirical analysis. The first source is the Living Standards Measurement Survey (*Encovi* for its acronym in Spanish) developed by the Guatemalan Statistics Bureau (INE). *Encovi* is a comprehensive, multi-purpos,e cross-sectional

[1] It is estimated that 83% of Guatemala's GDP is generated in areas expecially prone natural disasters.

household survey that collects information on a wide range of aspects covering the main demographic, social and economic characteristics of the population. The sample consists of approximately 13,500 households (equivalent to over 69,000 individuals) and is representative at the national, urban, rural, regional and state levels.[2] The survey is collected every 4 to 5 years between March and August, which means that the post-shock survey (2011) was fielded between 10 and 15 months after Agatha hit Guatemala, allowing for identification of its short- to medium-term impacts.

We pool the 2006 (pre-shock) and 2011 (after-shock) waves of *Encovi* to run a D-D analysis, which constitutes the basis for our research design (discussed in more detail in the next section). The two surveys used the same sampling frame drawn from the 2002 National Housing and Population Census[3] and collected data using the same field protocols and questionnaires. The same survey design for the two waves allows us to define a fully comparable set of variables before and after the shock. We construct outcome variables to measure household well-being (consumption and income per capita,[4] binary indicators to distinguish households below and above the national poverty threshold,[5] and measures to capture the depth and severity of poverty) as well as other dimensions through which households may have attempted to cope with the shock (adult and child labor supply, school participation and changes in asset ownership). The richness of the data also allows including as control variables a standard set of household-level socioeconomic and demographic characteristics.

The climate data –the second main source of information– was compiled from a historical registry administered by the Guatemalan Institute of Seismology, Volcanology, Meteorology

[2] Guatemala is administratively divided into eight regions and 22 states.

[3] The 2002 Census is comprised of 15,511 primary sampling units (PSUs) corresponding to 2,127,915 occupied dwellings. The sample for the survey consists of 1,184 (2006) and 1,200 (2011) PSU's –selected from random clusters of the 2002 Census– and 14,400 dwelling or secondary sampling units (SSU's), selected randomly within the cluster. The PSU's overlap in 2006 and 2011.

[4] Household expenditures captured in the survey include expenses on food, rent, durable goods, payment of basic services and education, and health services. Unit prices to value the official consumption basket to measure poverty are obtained from the household questionnaire. A consumption price index is constructed to account for geographical differences across municipalities. In 2011, the Guatemalan Statistics Bureau (INE) modified the methodology to construct the consumption aggregate for households, making it incomparable with the consumption measure produced in 2006. To ensure full comparability, we applied the same methodology (2006 definition of the consumption aggregate) to both years.

[5] Guatemala uses consumption as the welfare indicator to measure poverty based on two official poverty lines: 9 Quetzales/person/day for extreme poverty and 18 Quetzales/household/month for moderate poverty in 2006. The values for 2011 correspond to 12 and 25, respectively. The extreme poverty represents the cost of acquiring the minimum calories required to sustain life. The value of the moderate poverty line accounts for a minimum consumption of basic goods and services.

and Hydrology (*Insivumeh*). This system keeps records on daily and monthly rainfall and temperature from 1963 to 2013 for a grid of 73 weather stations scattered across the country.[6] However, many stations operated only for a short period of time. Consequently, in order to gauge more reliable estimates of historical rainfall patterns across geographic areas, we used information from the 39 stations that recorded weather data uninterruptedly from 1980 to 2010 (see Figure 2 for a detailed description of the coverage of the climate data).[7] Additionally, we constructed shock measures using a slightly larger subset of weather stations (42 stations with monthly rainfall data for the period 1990-2010) to check the consistency of both the treatment status assigned to each municipality (treated vs. comparison or alternatively high- vs. low-intensity rainfall due to Agatha) and the base empirical results resulting from a balanced panel of weather stations for the period 1980-2010.

We complement the precipitation data from *Insivumeh* with weather records from 15 other stations owned by the Guatemala Sugarcane Association (*Cengicaña*). These stations are geographically located in southern Guatemala, the area most affected by Agatha. Overall, the density of weather stations is larger in this part of the country. This is expected to increase the accuracy of rainfall measurement, something important considering that the south is more mountainous.. The average distance from the municipalities to the closest weather station in our final sample of analysis is 19 kilometers (kms) (s.d. = 12 kms). Finally, 327 municipalities in *Encovi* were matched[8] to the closest weather station to determine their historical rainfall in the month of May and allocate the treatment.

4. Identification Strategy

The identification of the causal effects of the 2010 Agatha storm on household welfare exploits the time and spatial variation in the trajectory and intensity of the shock across the Guatemalan territory in a D-D analysis. More specifically, our empirical strategy relies on the comparison, before and after the 2010 Agatha storm, of the outcomes of interest (for instance, per capita consumption or poverty incidence) between the more-affected (treated) and less- or

[6] Daily rainfall and temperature data are patchy across stations in the registry so we use records on monthly averages which are more complete in the dataset.
[7] Only one out of the 73 stations has been recurrently active during the whole period.
[8] The algorithm to match a station to a municipality calculates the centroid (i.e. the average position of all the points in a shape) of the polygon that represents a municipality and finds the nearest weather station (linear distance controlling for the earth's curvature). The maximum distance is 85 km and the minimum is less that 1km.

non-affected (comparison) households. The standard assumption underlying the validity of our estimates is that differences between the treatment and comparison groups would have remained constant in the absence of Agatha. As discussed in more detail in the following section, we confirmed the validity of this assumption using two waves of household data spanning a period before the shock.

Considering the nature of the event analyzed in the paper, a key element of our research design is the treatment (i.e. shock) allocation mechanism to classify the units of analysis between affected and less- or non-affected households. Following applications in the climatology literature, we construct measures of standardized precipitation anomalies recorded in May 2010 for each weather station to identify areas that experienced extreme rainfall shocks due to Agatha (Heim 2002; Keyantash and Dracup 2002). These measures capture the number of standard deviations away from the long-term (1980-2010) mean for each station. For the base empirical models we define excessive rainfall shocks as standardized precipitation anomalies that are 2 or more standard deviations above the historical mean, a typical threshold used in the literature. The treatment status of the households is thus coded by a binary variable (Rain Shock = 1 for affected households, = 0 otherwise) determined by the standardized precipitation anomaly of the closest weather station. In the robustness section we also discuss the sensitivity of the results to definitions of precipitation anomalies that take as a reference the long-run median rather than the mean.

The base empirical models are estimated with the following specification:

(1) $$Y_{imt} = \alpha_m + 2011_t + \beta_1 \text{Rain Shock}_{\text{mt}} + X_{imt}'\gamma + \varepsilon_{imt} \qquad t=2006, 2011$$

where Y_{imt} denotes the outcome of interest (for instance, household consumption or poverty status) for household *i* living in municipality *m* in period *t*; 2011_t is a year fixed effect that controls for the average changes in the welfare outcome of households across all municipalities between 2006 and 2011; α_m are municipality fixed effects that control for time-invariant municipality characteristics and Rain Shock_{mt} is a binary variable that identifies households located in the most affected municipalities in 2011. All regressions also control for a vector of household-level characteristics X_{imt} that are not expected to be affected by the shock but are likely to influence household consumption and include age, gender, years of education, marital status and race of the household head as well as location (urban or rural). Finally, ε_{imt} is a random, idiosyncratic error term. β_1 is the (reduced-form) parameter of interest.[9]

In order to better fit the distribution of the precipitation generated by the disaster and improve the measurement of the shock, we also estimate models that take into account the varying strength of the event. To do so, affected households are classified into low-, medium- and high-intensity groups if the standardized precipitation anomaly in May, 2010 falls between 2 and 3, 3 and 5 and more than 5 standard deviations away from the long-term mean, respectively. For these models, however, the definition of the comparison group stays the same as that used in equation (1). The econometric specification for the treatment dose analysis is as follows:

$$\text{(2)} \qquad Y_{imt} = \alpha_m + 2011_t + \beta_2 \text{Low}_{mt} + \beta_3 \text{Medium}_{mt} + \beta_4 \text{High}_{mt} + X_{imt}'\gamma + \varepsilon_{imt}$$

where Low_{mt}, Medium_{mt}, and High_{mt} are binary variables to capture the sub-treatment groups. In this case, the parameters of interest are β_2, β_3, and β_4. Results from estimating (1) and (2) are presented in the next section.

A threshold of two standard deviations may be an arbitrary cutoff to accurately capture excessive (damaging) rainfall. In addition to the level of precipitation, the occurrence, magnitude and duration of floods are also determined by geological, topological and hydrological characteristics of the area under analysis. Our empirical models control for municipality fixed effects and thus could partly account for these factors. Notwithstanding that, concerns of measurement error in the way that the precipitation anomalies are defined may remain. To explore this, we test the ability of the shock measure to predict the actual manifestation of floods in the aftermath of Agatha. Yet, the flood data available have two caveats. They include only those events reported by local authorities –possibly missing some floods in a nonrandom fashion– and do not say anything about the intensity of the floods[10]. We run models with the probability of a municipality reporting at least one flood as the dependent variable and the standardized rainfall recorded in May 2010 and surface area of the municipality as regressors. We observe a strong and statistically significant association between the continuous shock measure and the occurrence of at least one flood in a

[9] In all regressions, the standard errors are clustered at the municipality level to allow for correlation across households within a municipality.

[10] The information contains geo-referenced incidents recorded by the National Coordinator for Disaster Reduction (CONRED) and the Secretary of Planning (SEGEPLAN) for the period 2008-2011. It allows identifying the type of incident (e.g. flood) as well as whether the event was caused by Agatha.

municipality. An increase of a standard deviation above the historical rainfall mean due to Agatha is associated with an increase of 26 percentage points in the probability of a municipality reporting a flood (Table 1). Similarly, a map that crosses the geographical location of municipalities and the floods shows a larger concentration of events in treatment municipalities (Figure 1).

Table 2 presents summary statistics of baseline key demographics and socioeconomic variables –including pre-shock means of the outcomes under analysis– for treated and control households. Balancing tests in the top panel of the table reveal that for a subset of variables, the differences between the two groups at baseline are statistically significant. The size of the differences is chiefly explained by the fact that a larger proportion of urban households are located in highly affected areas. Whereas some baseline statistical differences remain even after breaking down the sample by area, their economic significance is low and unlikely to confound the results. For instance, the average size of control households is 0.23 members smaller than treatment households (4.36 v. 4.59). Similarly, 92% of the control households have access to electricity, slightly less (95%) than the treatment group. Moreover, the central outcome variables analyzed in the paper (consumption per capita and poverty incidence) are fully balanced for the two groups at baseline. Notwithstanding that, we ran some specifications of the models with an array of cross-sectional time-invariant covariates to control for possible systematic differences between the two groups –including potential compositional changes over time– and to increase the precision of the estimates.

5. Empirical Analysis

5.1 Results

Household consumption and poverty

The analysis initially investigates the extent to which households that were severely hit by Agatha cut back their expenditures as a result of and/or to cope with the effects of the shock. In doing so, we first examine the evidence graphically looking at kernel estimates of the densities of consumption per capita (in logs) for affected (dashed lines) and non-affected households (dotted lines) (Figure 3).[11] The data (broken down by area) show that there were not large discrepancies in the densities of the treated and comparison groups at baseline (graphs at the top) and the graphs in the second row depict little differences between the estimated densities for the two groups. The story is rather different after the shock. As shown in the third row, there was a left-shifting of the entire density among households in urban areas affected by the shock compared to households in non-affected urban areas. In contrast, the densities for affected and non-affected households in rural areas behaved more or less similarly. Unconditional double differences of the densities for both groups over time (shown at the bottom of Figure 3) reveal that a greater share of treated urban households fell below the pre-shock median following the shock, providing suggestive evidence of negative impacts on consumption.

We formally test the observations emerging from the visual inspection of the empirical densities. Table 3 presents fixed-effects model estimates of the D-D estimator (β_1) from equation (1) following the binary treatment definition. The shock coefficient is statistically significant for the whole sample and for urban households (P-values of 0.014 and 0.001, respectively) but not for rural households. The point estimates indicate that consumption per capita fell on average by 69 quetzales (8.2% with respect to its pre-shock median value) among affected households (column 1, Table 3). The results in the whole sample are largely driven by the impacts observed among urban households. For these households, consumption per capita declined by 12.6% relative to the median consumption at baseline. Estimates from the treatment dose specification (equation 2) point to similar results. Household expenditures fell across the three categorical levels of precipitation anomalies (column 2, Table 3), again more strongly among urban households whose point estimates of the effect of Agatha are highly significant in a statistical and economic sense, showing a fall in consumption in the 9-14% range. Moreover, and giving credibility to the shock measure, the gradient between the intensity of the shock and the size of the impacts is evident in the whole sample and in the subsample of urban households.

The fall in consumption attributed to Agatha pushed some households into poverty. Linear

[11] Expenditures include the value of goods purchased, the estimated value of goods consumed from self- production, and the value of goods received as gifts from others. That is, the expenditure measure already reflects responses used by households to smooth consumption (such as receiving transfers, selling assets, or increasing labor supply).

probability models of the poverty headcount using the D-D model defined in equation (1) indicate that overall poverty increased by 3 percentage points or 7% (column 5, Table 3).[12] In line with the heterogeneity of the impacts on consumption, the result is driven entirely by a higher incidence of poverty in urban areas. Indeed, households in urban centers were 5.5 percentage points or 18% more likely to be poor after being hit by Agatha (p-value = 0.026). Roughly speaking, these effects translate into roughly 80,000 more families falling into poverty. Results from the treatment dose specification (equation 2) are also indicative of negative effects on poverty, particularly among households exposed to rainfall intensity Low (2<s.d.≤3) and High (s.d.≥5).

Finally, in trying to qualify the deterioration of household welfare in urban centers, we examined which expenditure items were more heavily compromised by the shock. We find statistically significant evidence that food expenditures among affected households fell by around 10% of the baseline level, accounting for close to 40% of the total reduction in consumption (Table 4). As a way of illustration, urban and rural poor households devote 42.3% and 47%, respectively, of their budget to food expenditures in the baseline sample. Unfortunately, there is not data to formally test whether households were able to protect calorie intake despite the lower expenditures by, for instance, substituting away from expensive calories towards cheaper calories. However, the existing literature on the relationship between income or expenditures and calories suggests that the effects on nutrition may not be trivial. Whereas estimates of calorie-income elasticities for developing countries vary considerably, largely due to methodological reasons, those obtained from calorie demand equations and identification strategies that address nonrandom measurement error and other possible biases fall within the 0.2-0.5 range (Strauss and Thomas 1995, Subramanian and Deaton 1996). Taking this range as a reference, the effect of Agatha implies that the consumption of calories would have fallen by 2% to 5% among affected households, equivalent to anywhere from 43 to 108 fewer calories per day based on the representative dietary energy consumption per capita of Guatemalans.[13] These results are not trivial. At 43.4%, stunting (low height-for-age z-score) in children 0-5 years of age at baseline was endemic nationally and equally high in urban settings (28.8%) at baseline (2008-2009 Maternal and Infant Health Survey).

[12] Compared to the consumption models, the analysis on poverty require stronger statistical power because only households crossing the poverty threshold provide variation useful to identify β_1 (equation 1) and β_2, β_3 and β_4 (equation 2).
[13] The daily dietary energy consumption per capita in Guatemala is estimated at 2,170 calories. Food and Agriculture Organization of the United Nations, February, 2009, "Compendium of food and agriculture indicators – 2006".

We also find that close to half of the total fall in consumption among urban households was due to a decline of nearly 80% in expenditures in durables, including items such as a stoves or refrigerators. Urban households also cut back on education-related expenses (around 13%) although –as will be discussed below—we do not observe that this led to an increase in dropout rates.

A regular argument in the literature on household risks and welfare is that the negative effects of shocks are typically larger among the poor. We looked at whether this was also the case in the context of Agatha. In the absence of household and/or individual panel data, we relied on estimates of municipal poverty rates in 2006 drawing from a poverty map jointly produced by the World Bank and INE. The subgroup analysis using different levels of poverty incidence did not support the notion that poverty at baseline is a strong predictor of the direction and magnitude of the effects.

Household income and adult labor supply

In trying to assess whether the fall in household consumption is itself the result of a persistent negative income shock triggered by the storm, we examine the effects of Agatha on household income per capita. In addition to collecting detailed consumption data, *Encovi* captured rich information on labor and non-labor income for all individuals in the household both before and after Agatha.

Similar to the analysis on consumption, we ran standard fixed-effects model specifications of the D-D estimator using the binary definition of the treatment. The results –summarized in Table 5– indicate that Agatha is associated with a reduction of household income per capita on the order of 10%, equivalent to 44.4 quetzales per capita per month. Effects estimated separately for urban and rural areas are also negative but not statistically significant. Unpacking the effects by income components reveals that the fall in total income is largely driven by a drop in income from labor, particularly from salaried jobs in urban areas, corresponding to 27% of the baseline median (third column of Table 5). Indeed, lower wage income among affected urban households helps explain nearly 70% of the decline in their household income per capita. The results also point to a fall in non-wage labor income in urban areas but, in constrast, point estimates are imprecise. Meanwhile, none of the point estimates for income components in the rural sample are statistically significant.

The econometric analysis provides evidence that the shock also influenced the labor supply of adults. We initially investigated if the decision of whether to work or not (extensive margin) changed to cope with the negative fluctuation in income brought by Agatha. The labor participation of all adults 17 to 65 years old is measured with an index variable that identifies economically active individuals that were employed or are actively looking for a job during the four weeks preceding the survey. Irrespective of the location (urban or rural) and gender of the individuals, econometric results from a linear probability model of equation 1 give no evidence of Agatha changing the decision to participate in the labor market in affected villages (Table 6). However, when focusing on the intensive margin, the analysis shows that adults from affected households, particularly men in urban centers, increased the number of hours worked in response to the shock. For the whole sample, adults that reside in affected areas appear to work 0.9 more hours per week in the aftermath of the event, amounting to an increase of 2.1 percent with respect to the baseline mean (approximately 42 hours/week). Once more such response is driven fully by the extra labor supply provided by male workers in urban centers, who worked on average for 2.5 hours more per week, raising their baseline labor supply (48 hours/week) by 5.3% (Table 6).

Finally, a fall in wages accompanied the increase in the number of hours of labor supplied, possibly signaling a sort of general equilibrium labor market effect produced by the shock. Employing the same empirical strategy, we find that hourly wages for the whole sample fell notably among workers in shock areas by 0.5 quetzales/hour, 5.4% with respect to the mean hourly wage at baseline (9.2 quetzales/hour) (results also shown in Table 6). As expected, the size of the wage effects is larger for urban workers with salaried jobs, for whom hourly wages fell by 9.3 percent. In line with the impact heterogeneity concerning the number of hours worked by female and male workers, the effects of the shock on wages only manifest among the latter.

Child school participation and labor

The existing literature has shown that households are often forced to withdraw children from school when confronted by idiosyncratic or systemic shocks (Baez et al. 2010). Natural disasters can disrupt schooling supply through the destruction of school facilities, increased absenteeism of teachers and limited physical accessibility, for instance, due to road damages. Furthermore, as shown above, household budget constraints can be aggravated by the shock, reducing the demand for education. Similarly, credit constrained households may also rely on the labor force of their children as an attempt to cope with the negative effects of the disaster.

We investigate the possibility of Agatha prompting these two household responses. Table 7 summarizes the results. Looking first at school attendance in the academic year preceding the survey –and using the same base empirical specification in equation 1– we find evidence that children aged 7 to 15 in areas that saw the largest rainfall were 2.2 percentage points (2.6%) less likely to attend school than children in the comparison group. Breaking down the impacts by area indicates that the reduction in school participation is explained by lower school attendance of children in rural areas, whose rate fell by 2.7 percentage points (p-value=0.073), equivalent to a reduction of 3.3% with respect to the level of enrollment at baseline. Subgroup analysis by gender (not shown) and age groups suggests that the negative impacts on school attendance affected boys, girls, young and older children more or less equally.

The results also reveal an increase in child labor force participation. We define a binary variable for children working or looking for a paid job as well as children engaged in non-paid work (e.g. domestic chores, child caring, etc.), which can be a mechanism for adults to free up time and further increase their own labor supply. Results show that children 7-15 years old in affected areas were 3.1 percentage points (10.8%) more likely to work in paid and non-paid activities over time relative to children in less affected regions (Table 7). In line with the geographic concentration of the negative impacts on school attendance, the effects on labor force participation are driven by households in rural villages that were hit by Agatha. Child labor increased by 4.2 percentage points or 12.8% of the pre-shock level among these households. However, contrary to what is seen for school attendance, the increase in the labor supply of children attributed to Agatha happened only among boys (result not shown) and mainly among those who were between 12 and 15 years old.

In order to check whether the extra labor supply in the extensive margin provided by children came at the cost of reducing their school participation, we ran models of the joint outcome for children enrolled in school at the beginning of the school year. We estimate the base D-D model on an outcome variable that is equal to one if the child works in paid or non-paid activities or is looking for a job, and also if the child is not attending school. The econometric results confirm that the increase in child labor force participation attributed to Agatha is mostly seen among children –predominantly boys– who also stopped attending school (Table 7). This set of results holds for the whole sample and for rural areas. In contrast, the proportion of children simultaneously working –or looking for a job– and attending school did not change over time in shock areas with respect to the comparison group, providing an indication that at the margin the added labor force of children reduced their school participation.

5.2 Robustness analysis

Additional empirical exercises confirm the robustness of the negative effects of the shock on the main variables of interest. We first test the central assumption underlying the internal validity of the identification strategy, namely whether or not the outcomes for affected and less- or non-affected households were systematically set on different pathways irrespective of Agatha. To do so, we pool two rounds of the *Encovi* data collected before the shock (2000 and 2006) to estimate placebo treatment effects of the shock on consumption and poverty. Overall, results of this "fake" binary treatment do not provide evidence of diverging trajectories preceding the shock between the treatment and control groups (Table 8- Panel A). The double-difference estimators for consumption per capita, poverty headcount and poverty gap are all statistically insignificant.[14]

In a second exercise we assess whether other forms of sample selection are likely to confound the results. Using pre- and post-shock data from 2006 and 2011, we run models to estimate placebo treatment effects on independent variables that capture household head characteristics –most of which are supposed to not be directly affected by the shock– such as age, education, gender, marital status and area of residence. Systematic changes in these pre-determined variables between the treatment and comparison groups could signal compositional changes such as endogenous migration and mortality. Nonetheless, results of this placebo test show that Agatha has no statistically significant relationship with any of the variables analyzed (Table 8- Panel B).

[14] Results for most of the other outcomes analyzed in the paper (not shown but available upon request) follow a similar pattern.

To further rule out concerns over sample selection produced by endogenous migration, we run econometric models of a binary migration variable that captures households that moved to another Guatemalan municipality after Agatha occurred against the shock measures and a subset of covariates.[15] The results from these models –and also from others that measure migration according to the location of both the household head and the spouse– do not provide evidence that Agatha pushed systematically more (or less) households to migrate away from the villages where they resided before the shock happened (Table 8- Panel C).

Another potential concern is the possibility of a systematic –as opposed to random– measurement error in the shock variable. More specifically, the empirical models may be picking up the cumulative and persistent effect of multiple rainfall shocks (floods and droughts) that occurred in the past if the location of those overlap closely with the geographic coordinates of Agatha's path. To investigate this bias in measurement, we checked if rainfall variability– including the occurrence and frequency of extreme events– in the pre-Agatha period (1970-2009) differ systematically between "affected" and "less- and non-affected" weather stations. To account for the different probability distribution of precipitation between the two groups of stations, we compute the coefficient of variation. The calculation of this normalized measure of dispersion shows that the coefficient of variation is comparable between treated (1.17) and control stations (1.12). Further, the geographical location of the precipitation anomalies of three large events that hit Guatemala in the 2000s (Hurricane Stan 2005, Tropical Storm Barbara 2008 and Hurricane Mitch 2008) does not overlap with the path of Agatha.

Another possible source of measurement error is the misallocation of historical rainfall and precipitation anomalies to households across municipalities. As noted before, municipalities are matched to their closest weather station. However, due to the low density of stations in some parts of the country, a subset of municipalities is paired with stations that are too far away to accurately track their rainfall patterns. For nearly 4% of households, the corresponding weather stations lie more than 50 kilometers away. We performed a sensitivity analysis restricting the sample to the rest of the households (96%) and rerun the consumption and poverty models of equation 1. The negative effects of Agatha on consumption and the associated increase in poverty not only hold in this subsample but are also more precisely

[15] It is worth noting that the *Encovi* surveys only track domestic migration.

estimated as reflected by the lower standard errors (Table 9).

Finally, and also related to potential issues of measurement error, the results appear to be robust to alternative definitions of the shock that are based on different critical thresholds (i.e. using different standard deviations), different computations of the z-score (using the historical mean and the median) and a continuous treatment (total rainfall recorded in May, 2010). Additionally, results do not change much when we re-estimate the main empirical models drawing from a larger balanced panel of weather stations (covering the period 1990-2011) to allocate households to the treatment and comparison groups based on alternative measures of long-term rainfall trends.[16]

5.3 Interpretation

Overall, the findings of this paper –in line with most of the existing evidence– highlight that the well-being of households is sensitive to the consequences of weather-related disasters. However, the results depart from existing research by documenting that relative to rural households, urban families appear to have carried the heaviest burden of the consequences of the shock –at least in terms of household consumption and poverty. The question is why were urban households disproportionally affected by Agatha? Unfortunately, data limitations make it difficult to empirically disentangle the mechanisms driving the impacts. Yet, in what follows we posit some informed hypotheses about the possible leading channels.

The first observation has to do with the magnitude of the shock itself. Whereas Agatha dropped record levels of rain across several parts of Guatemala, households located in urban areas experienced substantially stronger rainfall shocks compared to rural households. Household weighted mean standardized precipitation anomalies in urban and rural areas attributed to the shock were 3.7 and 3.0 z-scores, respectively. Nonetheless, the average masks large variation in excessive rainfall across areas. Figure 4 plots the density of the z-scores for affected households by area. It reveals that close to 40% of the households in urban centers were hit by rainfall levels that exceeded the historical mean by six or more standard deviations. We ran regressions of the base model (equation 1) on household consumption for the urban sample to spot impact heterogeneity for households that were exposed to rainfall anomalies of

[16] These results are not shown in the paper but are available from the authors upon request.

z-scores ≥ 6 relative to those with $2 \leq$z-scores ≤ 6. The results (shown in Table 10) offer suggestive evidence that the magnitude of the shock is associated with the spatial concentration and size of the impacts. Qualitatively speaking, treatment effects are consistently higher in magnitude for the group of z-scores ≥ 6 both in the national and urban samples.

Impact heterogeneity can also be traced back to the evolution of prices, likely influenced by the disruption in the functioning of markets following the disaster. Anecdotal assessment of the disaster suggests that the major damages to basic economic infrastructure and systems were registered in urban centers. We first examined the evolution of prices for an array of items tracked by Guatemala's National Statistics Institute (INE). While prices of many consumption items such as clothing, housing, recreation, health and education, among others, remained fairly stable, food prices began to rise right before the shock and this trend accelerated during the 10 months following Agatha. The cumulative increase in food prices 10 months after Agatha was 17 percent. Yet, even though it is not fully conclusive, breaking the data down by the lowest level of disaggregation (eight geographic areas[17]) is suggestive of higher price increases and volatility consistent with the geographic path of the shock (Figure 5). Regions such as *Sur Oriente* and *Noroccidente*, where nearly two-thirds of the households were affected, food prices increased by 65 and 20 percent, respectively. To further investigate the price channel, we derived implicit prices from the *Encovi* surveys for seven food items that account for over half of the basic food consumption basket that defines the national extreme poverty line. Using the price data as the response variable in a D-D framework shows steep statistically significant average price increases in treated urban areas for items such as milk (27%), sugar (16%), sugar (8%) and beans (6%). In contrast, prices appear much more stable in rural areas (Figure 6).

In contrast, the relatively low sensitivity of rural households to the negative effects of Agatha may be partly explained by the "favorable" timing of Agatha with respect to the local agricultural cycles in the areas flooded by the event. We use the 2003 Agricultural Census from the Ministry of Agriculture of Guatemala to map the main crops grown in the affected areas at baseline. Around 72% of the land cultivated corresponds to maize, beans, coffee and sugar cane, the two latter being permanent crops. The typical annual cycle of planting, growth and harvest of these four crops in Guatemala is shown in Table 11. As shown, the largest rainfall attributed

[17] Price data in Guatemala does not allow discriminating between urban and rural areas.

to Agatha occurred in late May, right in the middle of the seeding period of maize and beans. There is anecdotal evidence that the flooding damaged maize crops in some of the affected areas but not so much in others. In regard to coffee and sugar cane, the excessive precipitation fell well outside their traditional harvesting season. Using data from *Faostat* (FAO), we construct indices to track the annual production of these four crops in Guatemala during the period 2006-2012. While the production of sugar cane fell slightly after Agatha, consistent with our hypothesis, we do not observe a large drop in the annual yields of any of the four crops for the interval between the shock and the reference period covered by the *Encovi* survey (shown by the dotted vertical lines in Figure 7), ruling out supply shocks.

Finally, there is a possibility that formal social protection policy also played a role in partly shielding the basic welfare of rural families from the adverse effects of the shock. In April, 2008, the Government of Guatemala established and began implementing a standard Conditional Cash Transfer (CCT) program, *Mi Familia Progresa* (currently known as *Mi Bono Seguro*). The program transfers money to families living in poverty and extreme poverty that have children ages 0 to 15 years and/or pregnant women (or nursing mothers). A particular design feature of the program is that most of its beneficiaries are rural households.[18] At the time of Agatha, the CCT program benefited nearly 800,000 families, many of them located in parts of the country severely stricken by the floods. While it is possible that the cash transfers contributed to smooth basic consumption, the weak monitoring and enforcement of the school attendance conditionality –as reported by program managers– did not avoid that some children missed school. Yet, more analysis is necessary to sign the net effect from the interaction between the participation in the CCT program and the shock.

6. Conclusions

This paper provides robust evidence that Agatha, the strongest tropical storm to ever strike Guatemala since rainfall records have been kept, led to a sizable deterioration of human welfare among affected households. On average, per capita consumption fell by 5.5% in households matched to weather stations that recorded precipitation anomalies of two or more standard deviations from the historical mean during the days of the shock. While negative impacts triggered by excessive rainfall have been documented in the literature, most of the studies show

[18] There is also a fraction of program participant from marginal areas in the peripheries of urban centers.

that rural households are often disproportionally affected. Contrary to that, this paper illustrates that urban households can be as or more vulnerable when hit by extreme weather-related shocks. For these households, consumption per capita declined by 12.6% relative to the median consumption at baseline.

The negative effects of the shock span other areas of human welfare, particularly among urban households. The incidence of poverty increased by 5.5 percentage points, equivalent to 18% with respect to the poverty headcount that existed at baseline. Affected households cut back on expenditures on food by 10%, equivalent to a reduction of over 100 calories per day per household members. We also find evidence that households reduced expenditures on basic durables such as stoves or refrigerators.

Behind the limited ability of affected households to smooth consumption is a fall in income per capita of urban households on the order of 10%, driven mostly by a drop of labor income among salaried jobs. To cope with the shock, we find two different types of labor supply responses. First, male adults adjusted on the intensive margin by increasing the number of hours worked (1.9 hours more per week or 3.7%). This additional labor supplied occurred in tandem with a fall in the remuneration of workers, possibly signaling a sort of general equilibrium effect. Second, we find a sizable increase of 3.1 percentage points (10.8%) in child labor force participation –especially among boys in rural areas. Simultaneous to relying more on the labor force of their children, we find evidence that affected households were also more likely to withdraw them from school, raising the risk that they drop out.

A leading factor that helps to explain the sizable impact heterogeneity across areas is the strength of the shock itself. Impact studies often fail to quantify and map the intensity of natural shocks to the units of analysis. Our evidence suggests that part of the reason as to why the negative effects were more concentrated among urban households has to do with the fact that excessive precipitation was much stronger in urban areas. We also observe some evidence that food prices increased after the shock in parts of the region that saw the largest precipitation anomalies, especially in urban centers. At the same time, the relatively low sensitivity of rural households to the shock may be partly explained by the timing of Agatha with respect to local agricultural cycles. For the most part, the excessive precipitation fell in a period of the harvesting season that was not harmful for maize, beans, coffee and sugar cane, the main crops grown in affected areas. Finally, a large CCT program targeted mostly to rural households could have also helped protect their basic welfare in the aftermath of the shock.

A number of checks confirm the robustness of the findings to the trajectories of the outcomes preceding the shock between the treatment and control groups, endogenous compositional changes, nonrandom migration, possible issues of measurement error in the shock variable, alternative shock indicators based on different critical precipitation thresholds and different household-to-weather station matching criteria.

The magnitude of the effects documented in this paper is not trivial. In 2012, Guatemalan authorities reported an increase in the national poverty rate from 51% to 53.7% between 2006 and 2011. Government officials and most analysts have attributed such increase to the collateral effects of the global financial crisis. We, however, argue that this is only part of the story. Since a large fraction of households were bunched right above the poverty line before the shock, the fall in consumption per capita was enough to push nearly 80,000 additional families into poverty. Thus, this natural disaster is one of the key explanatory factors behind the increase in poverty recorded in urban Guatemala between 2006 and 2011. Ignoring the detrimental consequences of natural disasters on human welfare will limit the effectiveness development policy, in particular anti-poverty strategies.

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Table 1. Correlation between Floods Reported after Agatha and Treatment Status of the Municipality.

VARIABLES	Affected municipality (CONRED)
Z-score	0.026*
	[0.013]
Area	-0.000
	[0.000]
Constant	0.429***
	[0.055]

Observations: 333 municipalities.
Notes: Results from OLS regression. Standard errors in brackets
The Z-score indicates the number of standard deviations away from the rainfall mean (since 1980). Affected municipality is the probability of a municipality reporting a flood to CONRED in the aftermath of Agatha.
*** p<0.01, ** p<0.05, * p<0.1
Source: calculations by the authors based on data from Encovi (INE), Conred and Insivumeh.

Table 2. Summary Statistics at Baseline in 2006

	Treatment				Control				Significant
Variable	Obs.	Mean	Median	Std.error	Obs.	Mean	Median	Std.error	difference
Panel A: Total									
Size of Household	9247	5.04	5.00	0.03	4432	4.94	5.00	0.04	*
Urban	9247	0.46	0.00	0.01	4432	0.35	0.00	0.01	*
Total Consumption	9247	863	606	8.74	4432	812	579	12.62	*
Total Income	9215	1013	593	21.69	4416	968	541	31.33	
Moderate Poverty	9247	0.44	0.00	0.01	4432	0.47	0.00	0.01	*
Children 7-15 enrolled	9247	1.07	1.00	0.01	4432	1.04	1.00	0.02	
Panel B: Urban									
Size of Household	4237	4.59	4.00	0.03	1567	4.36	4.00	0.06	*
Total Consumption	4237	1104	793	15.24	1567	1061	807	25.06	
Total Income	4228	1351	802	38.38	1565	1484	836	63.08	
Moderate Poverty	4237	0.30	0.00	0.01	1567	0.31	0.00	0.01	
Children 7-15 enrolled	4237	0.93	1.00	0.02	1567	0.92	1.00	0.03	
Panel C: Rural									
Size of Household	5010	5.42	5.00	0.04	2865	5.26	5.00	0.05	*
Total Consumption	5010	660	502	9.21	2865	676	489	12.19	
Total Income	4987	726	455	23.44	2851	685	419	31.00	
Moderate Poverty	5010	0.56	1.00	0.01	2865	0.56	1.00	0.01	
Children 7-15 enrolled	5010	1.19	1.00	0.02	2865	1.10	1.00	0.02	*

Notes: Summary statistics with differences between treatment and control tested for significance. Total Consumption is the monthly expenditure p.c. of a household in Quetzales of 2006. Moderate poverty means that the p.c. expenditure is under the moderate poverty line. Total income is the sum of labor and non-labor incomes per month per capita. * p<0.05
Source: calculations by the authors based on data from Encovi (INE) and Insivumeh.

Table 3. Impacts on Total Consumption and Poverty

	Total Consumption		*Moderate Poverty*		*Extreme Poverty*	
Measure of Shock	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Total						
t * (rainfall z-score> 2)	-69.036**		0.030		-0.002	
	[27.814]		[0.019]		[0.018]	
t * (2 < rainfall z-score <= 3)		-50.806		0.023		-0.004
		[37.537]		[0.024]		[0.022]
t * (3 < rainfall z-score<= 5)		-71.968**		0.035		-0.011
		[29.671]		[0.024]		[0.020]
t * (rainfall z-score >= 5)		-84.366		0.029		0.014
		[53.776]		[0.025]		[0.021]
Baseline Mean/Median	598.8	598.8	0.453	0.453	0.112	0.112
Panel B: Urban						
t * (rainfall z-score> 2)	-181.140***		0.055**		0.000	
	[44.103]		[0.025]		[0.010]	
t * (2 < rainfall z-score <= 3)		-179.968**		0.085***		0.020*
		[89.900]		[0.030]		[0.012]
t * (3 < rainfall z-score<= 5)		-167.649***		0.025		-0.023
		[48.588]		[0.033]		[0.014]
t * (rainfall z-score >= 5)		-195.220***		0.070**		0.014
		[62.435]		[0.029]		[0.012]
Baseline Mean/Median	796.7	796.7	0.306	0.306	0.0469	0.0469
Panel C: Rural						
t * (rainfall z-score> 2)	8.584		0.015		-0.009	
	[34.086]		[0.027]		[0.028]	
t * (2 < rainfall z-score <= 3)		29.077		-0.015		-0.019
		[36.608]		[0.032]		[0.032]
t * (3 < rainfall z-score<= 5)		-17.423		0.048		-0.004
		[37.397]		[0.034]		[0.032]
t * (rainfall z-score >= 5)		25.569		0.003		0.003
		[72.903]		[0.044]		[0.046]
Baseline Mean/Median	496.9	496.9	0.561	0.561	0.159	0.159

Observations: 26,587 Total; 11,225 Urban; 15,362 Rural. *Notes*: Results from diff-diff regression controlling for age, gender, years of education, marital status and race of the household head as well as location (urban or rural). Robust standard errors in brackets clustered at the municipality level. Total Consumption is the monthly expenditure p.c. of a household. Quetzales of 2006. For Total consumption the baseline median is presented. Moderate poverty means that the p.c. expenditure is under the moderate poverty line. Extreme poverty means that the p.c. expenditure is under the extreme poverty line. For poverty the baseline mean is presented. The Z-score indicates the number of standard deviations above the rainfall mean (since 1980). t is the before-after dummy. *** p<0.01, ** p<0.05, * p<0.1.
Source: calculations by the authors based on data from Encovi (INE) and Insivumeh.

Table 4. Impacts on Consumption Components

Measure of Shock	*Food* (1)	*Health* (2)	*Education* (3)	*Durables* (4)
		Panel A: Total		
t * (rainfall z-score> 2)	-16.054	0.828	-5.821**	-16.554*
	[10.956]	[2.683]	[2.559]	[9.231]
Baseline Median	283.5	3.314	4.103	7.869
		Panel B: Urban		
t * (rainfall z-score> 2)	-40.622**	-5.967	-8.830*	-51.447***
	[16.306]	[4.775]	[5.094]	[16.087]
Baseline Median	336.1	4.571	11.82	15.91
		Panel C: Rural		
t * (rainfall z-score> 2)	7.954	5.190*	-2.860	-3.366
	[14.200]	[2.986]	[2.292]	[8.135]
Baseline Median	250.4	2.481	1.961	4.378

Observations: 26,587 Total; 11,225 Urban; 15,362 Rural. Notes: Results from diff-diff regression controlling for age, gender, years of education, marital status and race of the household head as well as location (urban or rural). Robust standard errors in brackets clustered at the municipality level. Consumption on food, health services, education and durable goods are monthly p.c. terms in Quetzales of 2006. The Z-score indicates the number of standard deviations above the rainfall mean (since 1980). t is the before-after dummy. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: calculations by the authors based on data from Encovi (INE) and Insivumeh.

Table 5. Impacts on Income per Capita (Total and by Components)

Measure of Shock	*Total Income Per Capita* (1)	*Labor Income Per Capita* (2)	*Labor income from salary work* (3)	*Non-wage income* (4)	*Non-Labor Income Per Capita* (5)	*Private Transfers Per Capita* (6)	*Public Transfers Per Capita* (7)	*Other non-labor income* (8)
				Panel A: Total				
t * (rainfall z-score> 2)	-44.4*	-52.4**	-33.6**	-18.8	12.4	2.9	0.6	-2.9
	[26. 2]	[21.6]	[14.4]	[12.9]	[9.0]	[6.0]	[0.9]	[11.4]
Baseline Mean/Median	566.6	391.7	198.4	46.3	20.50	69.9	10.8	78.3
				Panel B: Urban				
t * (rainfall z-score> 2)	-57.4	-51.9*	-35.7**	-16.2	28.4**	7.2	1.1	-9.6
	[40.7]	[30.4]	[18.1]	[23.1]	[12.6]	[9.5]	[1.0]	[23.6]
Baseline Mean/Median	781.7	556.3	326.2	35.4	15.740	70.8	7.2	142.7
				Panel C: Rural				
t * (rainfall z-score> 2)	-13.7	-22.1	-12.5	-9.6	6.8	2.3	-0.2	1.5
	[30.0]	[23.4]	[16.0]	[14.7]	[10.4]	[7.6]	[1.3]	[6.9]
Baseline Mean/Median	438.6	289	126.5	50.1	23.4	69.2	13.4	31.8

Observations: 26,163 Total; 10,905 Urban; 15,258 Rural.

Notes: Results from diff-diff regression controlling for age, gender, years of education, marital status and race of the household head as well as location (urban or rural). Robust standard errors in brackets clustered at the municipality level. All quantities are monthly p.c in Quetzales of 2006. All median baseline values are presented in all cases except for private transfers, public transfers and other non-labor income that the mean baseline value is presented. The Z-score indicates the number of standard deviations above the rainfall mean (since 1980). t is the before-after dummy.***p<0.01,**p<0.05,*p<0.1.

Source: calculations by the authors based on data from Encovi (INE) and Insivumeh.

Table 6. Impacts on Labor Income and Labor Supply

Sub-groups	*Working* (1)	*Hours Worked* (2)	*Hourly Wage* (3)
Panel A: Total			
Total	0.000	0.876	-0.505**
	[0.007]	[0.702]	[0.249]
Men	-0.002	0.874	-0.707**
	[0.005]	[0.694]	[0.305]
Women	0.010	1.049	-0.028
	[0.013]	[1.014]	[0.314]
Panel B: Urban			
Total	0.003	1.990**	-0.886**
	[0.013]	[0.864]	[0.352]
Men	0.002	2.514***	-1.031**
	[0.013]	[0.945]	[0.493]
Women	0.005	1.471	-0.561
	[0.017]	[1.281]	[0.554]
Panel C: Rural			
Total	-0.007	0.353	-0.112
	[0.008]	[0.959]	[0.307]
Men	-0.004	0.394	-0.294
	[0.005]	[0.936]	[0.352]
Women	-0.009	0.375	0.475
	[0.019]	[1.563]	[0.426]

Observations: 55,194 Total; 23,323 Urban; 31,871 Rural. 58% are men. 23% do not report wage.

Notes: Results from diff-diff regression on the sample of all adults 17 to 65 years old controlling for age, gender, years of education, marital status and race of the household head as well as location (urban or rural). Robust standard errors in brackets clustered at the municipality level. Working represents the binary variable that identifies economically active individuals that were employed or are actively looking for a job during the four weeks preceding the survey. Hours worked per week. Hourly wage per week in Quetzales of 2006.

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

Source: calculations by the authors based on data from Encovi (INE) and Insivumeh.

Table 7. Impacts on Children's Schooling and Labor Force Participation

	School Attendance			*Labor force participation*		
	7 to 15	*7 to 11*	*12 to 15*	*7 to 15*	*7 to 11*	*12 to 15*
Measure of Shock	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Total						
t * (rainfall z-score> 2)	-0.022*	-0.028**	-0.017	0.031*	0.020	0.047*
	[0.012]	[0.013]	[0.017]	[0.018]	[0.016]	[0.027]
Observations	33,022	18,977	14,045	33,222	12,464	9,028
Baseline Mean	0.833	0.906	0.782	0.183	0.101	0.300
Panel B: Urban						
t * (rainfall z-score> 2)	0.006	0.002	0.010	-0.021	-0.023	-0.020
	[0.018]	[0.017]	[0.031]	[0.022]	[0.019]	[0.038]
Observations	11,530	6,513	5,017	11,599	6,515	5,084
Baseline Mean	0.886	0.937	0.855	0.136	0.0644	0.233
Panel C: Rural						
t * (rainfall z-score> 2)	-0.027*	-0.035**	-0.022	0.042*	0.030	0.061*
	[0.015]	[0.015]	[0.021]	[0.023]	[0.023]	[0.033]
Observations	21,492	12,464	9,028	21,623	12,461	9,162
Baseline Mean	0.804	0.890	0.742	0.236	0.120	0.374

Notes: Results from diff-diff regression controlling for age, gender, years of education, marital status and race of the household head as well as location (urban or rural). Robust standard errors in brackets clustered at the municipality level. Unit of observation are the children surveyed in ENCOVI 2006 and 2011. The Z-score indicates the number of standard deviations above the rainfall mean (since 1980). t is the before-after dummy.

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

Source: calculations by the authors based on data from Encovi (INE) and Insivumeh.

Table 8. "Fake" Treatment Effects (Panels A and B) and Migration Analysis (Panel C)

Measure of Shock	*Total Consumption* (1)	*Health* (2)	*Education* (3)	*Moderate Poverty* (4)	*Extreme Poverty* (5)
Panel A: Results using Encovi 2000					
t * (rainfall z-score> 2)	-36.633	-9.020*	0.334	-0.023	0.017
	[41.047]	[4.797]	[3.136]	[0.030]	[0.019]
Baseline Mean	957.0	34.53	40.87	0.459	0.106
Panel B. Results on pre-determined variables					
Measure of Shock	*Education* (1)	*Age* (2)	*Gender* (3)	*Area of residence* (4)	*Single-married* (5)
t * (rainfall z-score> 2)	-0.238	-0.086	0.014	0.013	0.009
	[0.154]	[0.378]	[0.011]	[0.024]	[0.011]
Baseline Mean	3.966	45.47	0.788	0.424	0.792

Panel C. Results on migration

Measure of Shock	*HH Head moved less than 1 year ago/Born in different municipality* (1)	*HH Head and spouse moved less than 1 year ago/Born in different municipality* (3)
t * (rainfall z-score> 2)	0.001	-0.002
	[0.003]	[0.002]
Baseline Mean	0.0131	0.00690

Observations: 20,788 Panel A; 23,320 Panel B; 26,587 Panel C.

Notes: Results from D-D regression controlling for age, gender, years of education, marital status and race of the household head as well as location (urban or rural). Robust standard errors in brackets clustered at the municipality level. Pre-treatment placebo refers to the D-D methodology applied to Encovi 2000 and Encovi 2006. The Z-scores indicates the number of standard deviations above the rainfall mean (since 1980). t is the before-after dummy.

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

Source: calculations by the authors based on data from Encovi (INE) and Insivumeh.

Table 9. Effects of Agatha on Consumption and Poverty (Subsample of Households Located Less than 50 Kilometers Away from the Closest Weather Station)

	Total Consumption	*Moderate Poverty*
Measure of Shock	(1)	(2)
	Panel A: Total	
t * (rainfall z-score> 2)	-79.983***	0.033*
	[28.177]	[0.019]
Baseline Mean/Median	603.3	0.448
	Panel B. Urban	
t * (rainfall z-score> 2)	-176.094***	0.047*
	[44.263]	[0.025]
Baseline Mean/Median	799.4	0.303
	Panel C. Rural	
t * (rainfall z-score> 2)	-1.191	0.022
	[35.389]	[0.028]
Baseline Mean/Median	499.1	0.558

Observations: 25,803 Panel A; 11,021 Panel B; 14,782 Panel C.
Notes: Results from diff-diff regression controlling for age, gender, years of education, marital status and race of the household head as well as location (urban or rural). Robust standard errors in brackets clustered at the municipality level. Baseline median for Total Consumption and baseline mean for Moderate Poverty. The Z-score indicates the number of standard deviations above the rainfall mean (since 1980). t is the before-after dummy.
*** p<0.01, ** p<0.05, * p<0.1.
Source: calculations by the authors based on data from Encovi (INE) and Insivumeh.

Table 10. Effects of Agatha on Consumption and Poverty (Subsample Household Exposed to Precipitation Anomalies of z-scores≥6)

	Coef	*CI 90%*	*CI 90%*
	(1)	(2)	(3)
Panel A. Total			
Total Consumption			
t * (2 < rainfall z-score <= 6)	-54.03*	-100.09	-7.9
	[27.9]		
t * (rainfall z-score> 6)	-111.4**	-199.05	-23.8
	[53.1]		
Moderate Poverty			
t * (2 < rainfall z-score <= 6)	0.026	-0.007	0.06
	[0.020]		
t * (rainfall z-score> 6)	0.034	-0.002	0.08
	[0.025]		
Panel B. Urban			
Total Consumption			
t * (2 < rainfall z-score <= 6)	-164.4***	-245.03	-83.9
	[48.8]		
t * (rainfall z-score> 6)	-206.6***	-308.7	-104.5
	[61.8]		
Moderate Poverty			
t * (2 < rainfall z-score <= 6)	0.044	-0.0006	0.09
	[0.027]		
t * (rainfall z-score> 6)	0.071**	0.0223	0.1196
	[0.029]		

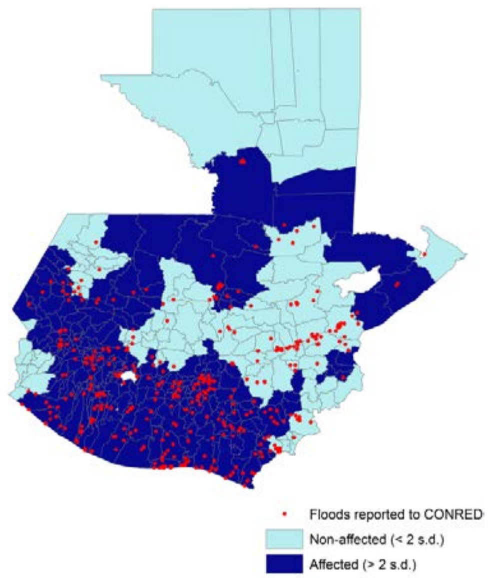
Observations: 26,587.
Notes: Results from diff-diff regression controlling for age, gender, years of education, marital status and race of the household head as well as location (urban or rural). Robust standard errors in brackets clustered at the municipality level.
The Z-score indicates the number of standard deviations above the rainfall mean (since 1980). t is the before-after dummy.
*** p<0.01, ** p<0.05, * p<0.1
Source: calculations by the authors based on data from Encovi (INE) and Insivumeh.

Table 11. Agricultural Cycle of Main Crops in Areas Affected by the Shock

	Agricultural land in affected areas	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Maize	38%					P			H				
									p			h	
Beans						P			H				
										p			h
Coffee	22%	H									H		
Sugar Cane	13%	H and P										H	

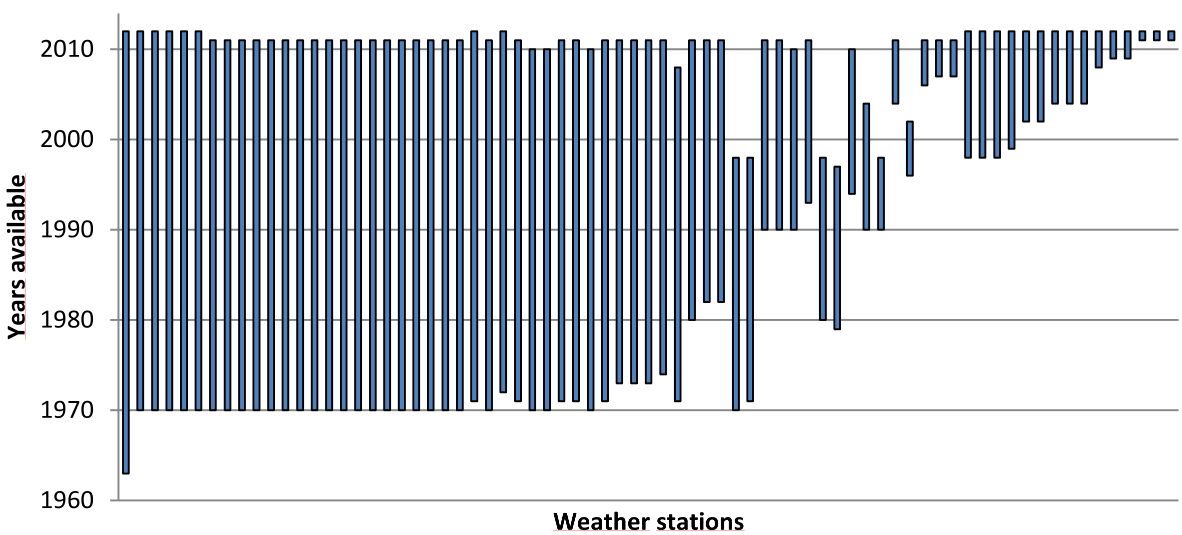
Note: H = first harvesting season; P = first planting season; h = second harvesting season; p = second planting season. Vertical gray bar corresponds to the timing of the Tropical Storm
Source: Guatemalam Department of Food Security.

Figure 1. Map of Floods Reported after Agatha and Treatment Status of the Municipalities



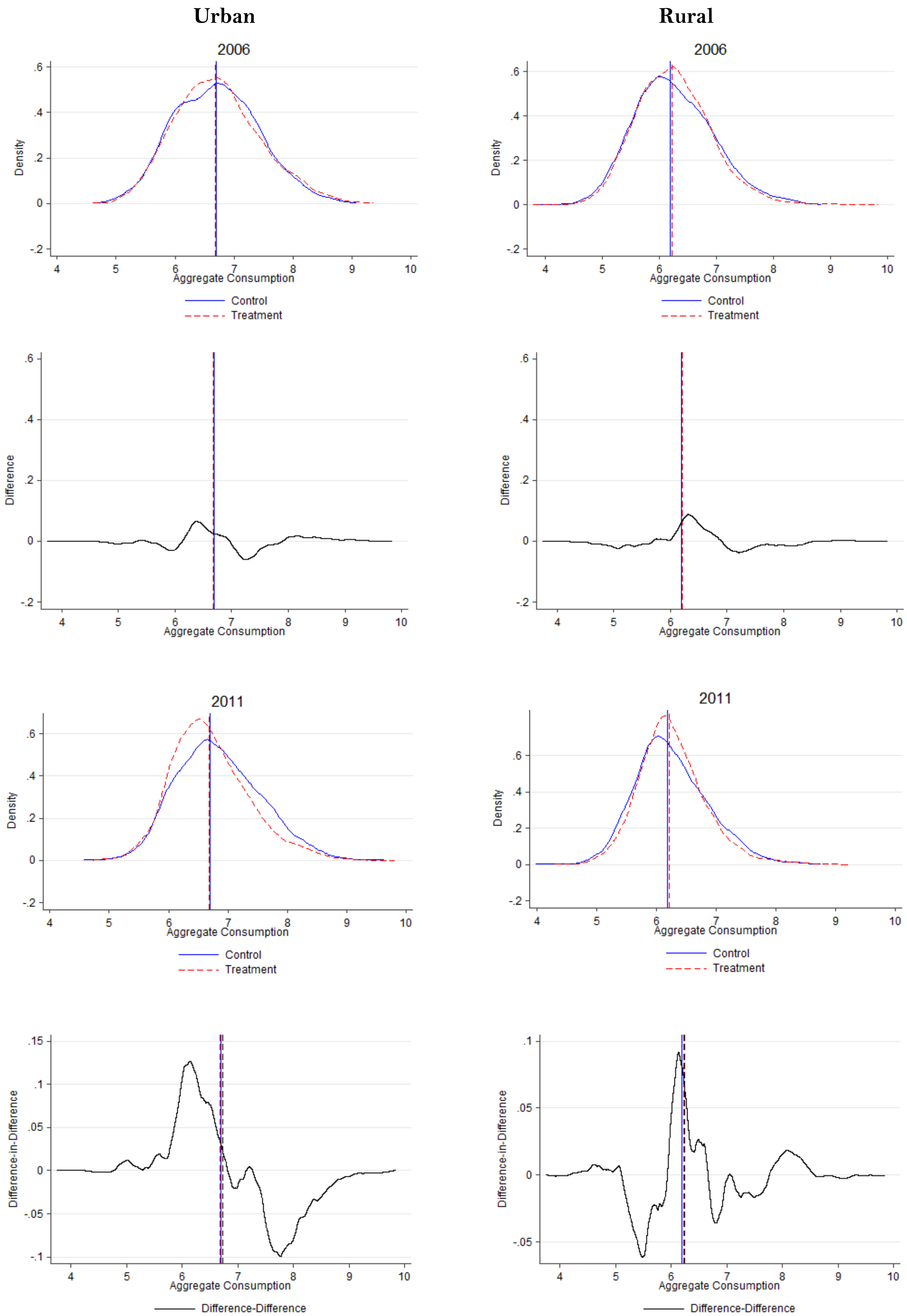
Notes: The red dots represent each flood reported to CONRED in the aftermath of the storm. The darker blue polygons represent affected municipalities.
Source: calculations by the authors based on data from CONRED and Insivumeh.

Figure 2. Coverage of Weather Stations in Guatemala



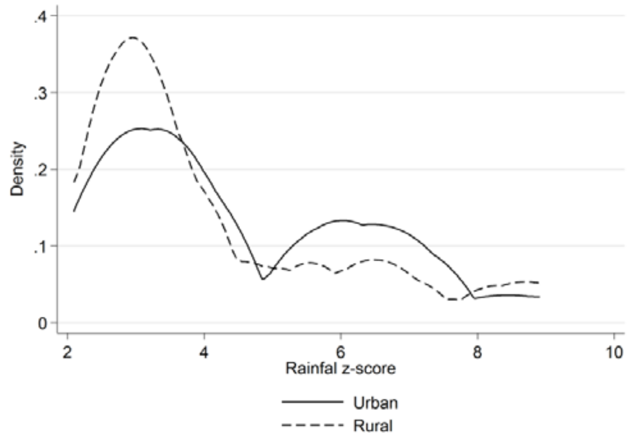
Notes: The graph illustrates the years for which rainfall information is available in each weather station of the combined INSIVUMEH and CENGICAÑA grid.
Source: calculations by the authors based on data from Insivumeh and Cengicaña.

Figure 3. Kernel Estimates of the Density Functions of Household Consumption per Capita



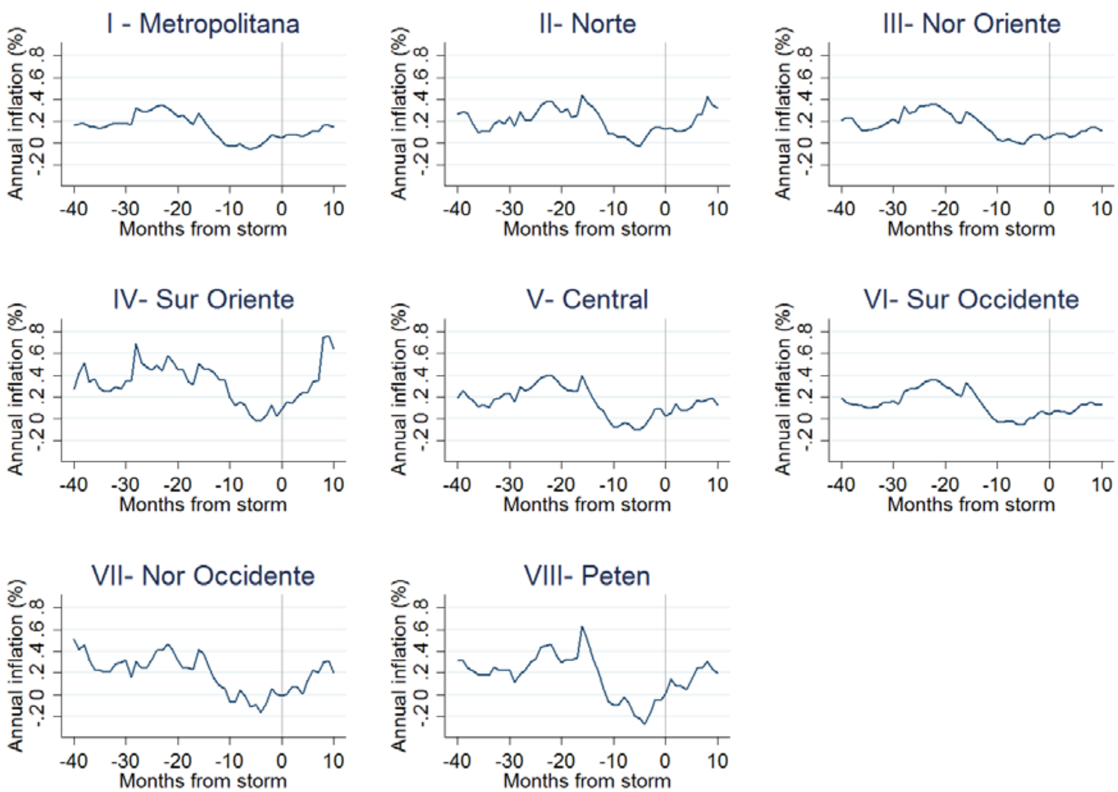
Note: Epanechnikov kernel of total household consumption per capita.
Source: calculations by the authors based on data from Encovi (INE) and Insivumeh.

Figure 4. Distribution of Rainfall Z-score in May 2010



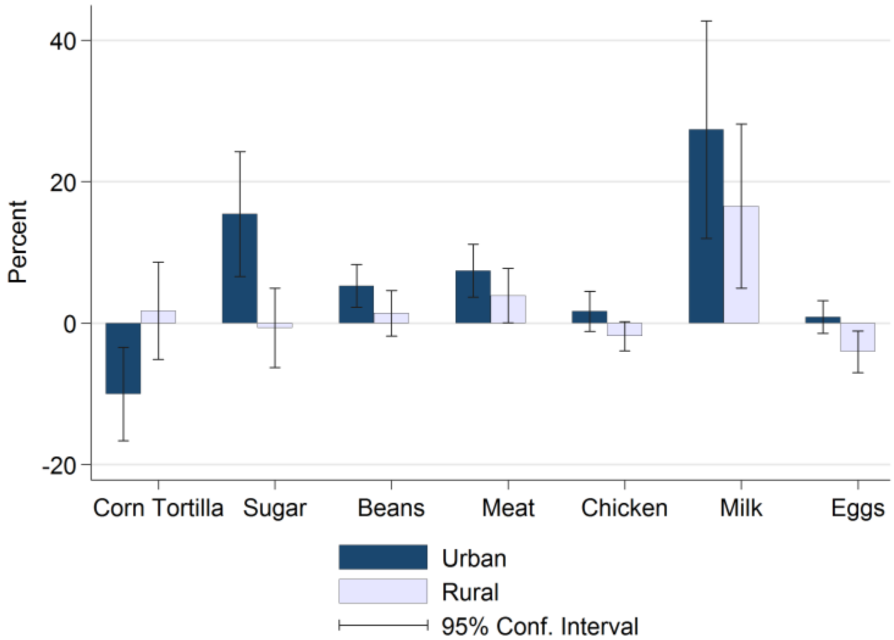
Source: calculations by the authors based on data from Insivumeh.

Figure 5. Food Price Index by Geographical Regions



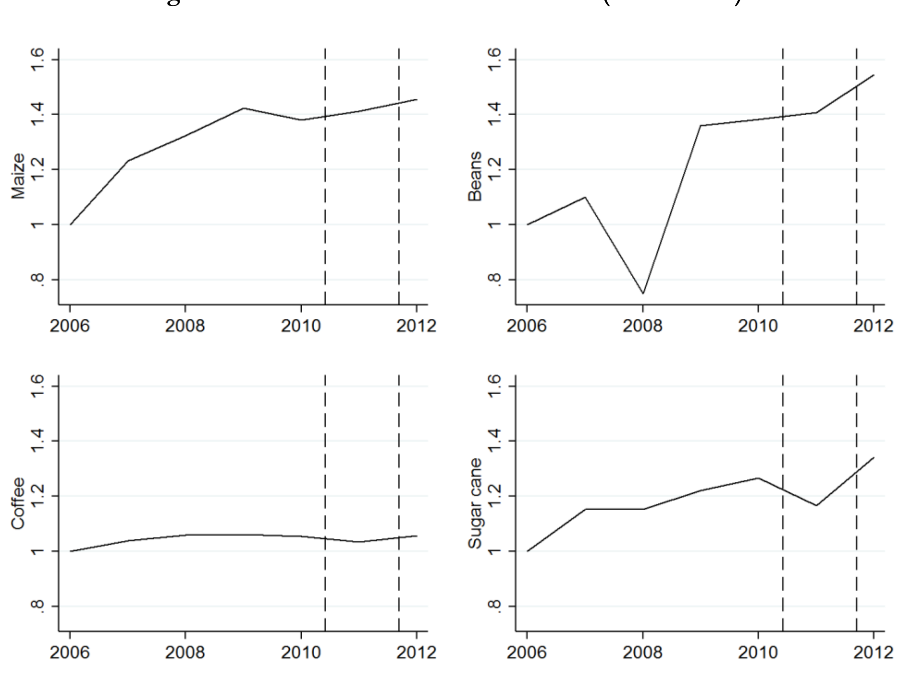
Notes: vertical line denotes the timing of the shock.
Source: calculations by the authors based on price indices by INE.

Figure 6. Treatment Effects on the Prices of Selected Food Items



Notes: Point estimates from econometric regressions specified as models in Table 1. Robust standard errors clustered at the municipality level.
Source: calculations by the authors based on data from Encovi (INE) and Insivumeh.

Figure 7. Annual Domestic Production (2006-2012)



Notes: dotted line denotes the interval of time covered in the analysis
Source: Calculations by the authors based on data from Faostats (FAO).