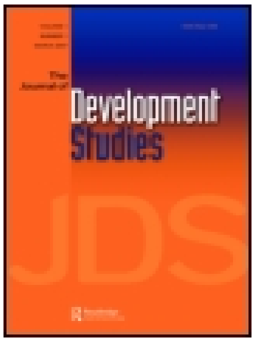

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Gone with the Storm: Rainfall Shocks and Household Wellbeing in Guatemala

JAVIER E. BAEZ*,**, LEONARDO LUCCHETTI*, MARIA E. GENONI*
& MATEO SALAZAR*
*World Bank, Washington, DC, USA, **Institute for the Study of Labor (IZA), Bonn, Germany

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ABSTRACT *This paper identifies the negative consequences of the strongest tropical storm ever to strike Guatemala on household welfare. Per capita consumption fell in urban areas, raising poverty substantially. Households cut back on food consumption and basic durables, and attempted to cope by increasing their adult and child labour supply. The mechanisms at play include the intensity of the shock, food prices and the timing of Agatha with respect to local harvest cycles. The results are robust to placebo treatments, migration and measurement error, and partly explain the increase in poverty in the country previously attributed solely to the collateral effects of the global financial crisis.*

1. Introduction

Largely motivated by the ongoing debate on global warming, the influence of climate factors on economically relevant outcomes is increasingly drawing more scientific attention. With temperatures expected to continue rising and projections showing 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 wellbeing of households (and assessing how they cope with these risk factors) is more challenging while being central to more fully estimate the economic impact of such shocks and design effective risk management strategies.

The last few years have seen the rise of a large body of empirical research on the subject (see Baez, de la Fuente, & Santos, 2010; Dell, Jones, & Olken, 2014for surveys of this literature). Three main messages seem to emerge from the existing literature. First, households enact numerous strategies for dealing with extreme weather but overall their mitigation capacity is insufficient for the task of maintaining – let alone improving – their welfare. Excess rainfall and droughts have been found to halve crop income and reduce consumption significantly among affected households (for example, Kazianga & Udry, 2006 for Burkina Faso) or forced them to deplete their productive assets (for instance, Dercon, 2004 for Ethiopia). The second observation pertains to the persistence of effects. The immediate negative consequences of weather shocks often carry over the longer term. Children who

Correspondence Address: Javier E. Baez, World Bank, 1818 H Street NW, Washington, DC 20433, USA. Email: jbaez@worldbank.org
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become stunted due to droughts or floods often do not fully recover later in life, resulting in lower school attainment and earnings in adulthood (for instance, Alderman, Hoddinott, & Kinsey, 2006 for Zimbabwe). Finally, there is remarkable impact heterogeneity. The evidence more often than not shows deprived populations often carry the heaviest burden (for instance, Del Ninno & Lundberg, 2005 for Bangladesh).

This paper looks at the vulnerability of household welfare to large rainfall shocks in a context where natural risks are prevalent and more than half of the population lives in poverty. More specifically, we exploit spatial and time variation in extreme (excessive) rainfall to 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 impacts across different groups of people and investigates the possible mechanisms at play.

The study finds that household welfare, measured by per capita consumption, fell among affected households on average by 7.7 per cent of the median consumption at baseline. Further inspection of the data shows that the losses in consumption attributed to the shock arose mostly among urban households, which experienced a decline of 12.6 per cent of their median consumption. Nearly half the drop in consumption was explained by a reduction in food expenditures of 12 per cent, between 45 and 110 fewer calories per person per day. Affected households also cut back expenditures on health services and durables, including basic items for household welfare, such as a stoves or refrigerators.

Storm Agatha pushed affected households below the poverty line, mostly in urban areas, where poverty increased by 5 percentage points (16%). Roughly speaking, these effects translate into 80,000 more families falling into poverty and partly explain the rise in poverty recorded for urban Guatemala between 2006 and 2011, which had been attributed solely to the collateral effects of the 2008 global financial crisis. The increase in poverty was largely driven by a fall in income per capita, mostly among salaried workers. In an effort to cope with the shock, adults – particularly urban men – increased their labour supply on average by two additional hours/week (4.7%). Similarly, the engagement of affected rural children in paid and unpaid work increased, which came at the cost of reducing their school participation (2.7%).

There was substantial heterogeneity in the strength of the shock between urban and rural areas. Agatha dropped relatively much more rain over urban areas, a factor partly underlying their larger negative impacts. There is also suggestive evidence that increases in food prices accelerated after the shock in the areas that recorded the largest precipitation anomalies, a process likely linked to limited accessibility to urban centers due to the destruction of infrastructure. In contrast, the lower sensitivity of rural households is partly explained by the fortuitous timing of Agatha in relation with the harvest cycles of the main crops. For the most part, the excessive precipitation fell in a period of the harvesting season that was not harmful for maize, beans, coffee or sugar cane, the main crops grown. Finally, cash transfers from a safety net program targeted mostly at rural households could have contributed to the protection of their basic welfare in the aftermath of the shock.

Overall, the results are fairly robust to several robustness checks, including tests on the underlying assumptions of the identification strategy, and to potential issues of endogenous migration and measurement error. The findings are in line with evidence from previous studies that have investigated the vulnerability of households to natural disasters in Guatemala (Bustelo, 2012; Hermida, 2010). Unlike these studies, our paper examines a shock that placed most of the burden on urban households.

The rest of the paper is structured as follows: Section 2 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 our identification strategy. Section 5 presents the empirical results, including discussion on robustness checks and our interpretation of the findings. Finally, Section 6 concludes.

2. National context and Tropical Storm Agatha

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

The geographic location of Guatemala makes it prone to frequent and high-intensity geological and weather-related shocks, such as earthquakes, volcanic eruptions, droughts, storms and hurricanes. The counry ranks fifth worldwide in terms of economic risk to natural hazards (CEPAL, BID, FMI, UNFPA, 2011).[1] Meanwhile, the Global Climate Risk Index puts Guatemala in 12th place worldwide according to the number of extreme weather events recorded between 1991 and 2010 – and in second 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 8 May 2010, Agatha originated as a tropical depression on 29 May 2010 in the eastern Pacific. A few hours later the tropical depression developed into a cyclone, making landfall in Champerico, southwest of Guatemala. The surface circulation of Agatha weakened as it continued northeastward into the Sierra Madre Mountains and it began to dissipate on 30 May 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 one hardest hit. Some parts of the country received over 900 millimeters of rainfall, the highest levels recorded in more than 60 years, making Agatha the strongest tropical cyclone ever to strike Guatemala since precipitation records began. Loss of life, destruction of homes, crops and critical infrastructure – including schools and health centres – and the subsequent disruption of economic and institutional systems forced government officials to declare a state of emergency in the affected ares. 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 damage amounted to 2.2 per cent of GDP. Donations centres across the country started deploying relief aid on 31 May but anecdotal evidence suggests that this assistance was far from sufficient to mitigate the immediate consequences of the disaster (CEPAL, BID, FMI & UNFPA, 2011).

3. Data

Two main sources of data underlie our empirical analysis. The first source is the Living Standards Measurement Survey (*Encovi* is its acronym in Spanish), developed by the Guatemalan Statistics Bureau (INE). *Encovi* is a cross-sectional household survey on a wide range of aspects covering the main demographic, social and economic characteristics of the population. It interviews approximately 13,500 households (over 69,000 individuals) and is representative at the national, urban, rural, regional and state levels.[2] The survey is collected every four to five years between March and August. This means that the post-shock survey (2011) was fielded 10–15 months after Agatha hit Guatemala, with a recall period that allows for the identification of its short- to medium-term impacts.

We pooled 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 same survey design for the two waves (sampling frame,[3] questionnaires and field protocols) allowed us to define a fully comparable set of variables before and after the shock. We constructed outcome variables to measure household wellbeing (consumption and income per capita,[4] and binary indicators to distinguish households below and above the national poverty threshold[5]) as well as other dimensions through which households may have attempted to cope with the shock (adult and child labour supply, school participation and asset ownership). The richness of the data also allowed controlling for a standard set of household-level socioeconomic and demographic characteristics.

The weather data was compiled from a historical registry administered by the Guatemalan Institute of Seismology, Volcanology, Meteorology and Hydrology (*Insivumeh*). This registry keeps records on daily and monthly rainfall and temperature from 1963 to 2013 for a grid of 73 stations across the country.[6] However, some stations operated for a shorter period of time. In order to gauge more reliable estimates of rainfall patterns across geographic areas, we used information from the 39 stations that recorded weather data uninterruptedly from 1980 to 2010 (see Figure A1 in the Online Appendix for a detailed description of the coverage of the climate data).[7] Shock measures were also constructed using a larger subset of stations (42 with monthly rainfall data for the period 1990–2010) to check the consistency of both the treatment status assigned to each municipality (high- versus low-intensity rainfall due to Agatha) and the sensitivity of the empirical results. The average distance from the municipalities to the closest weather station in our final sample of analysis was 19 kilometers (kms) (s.d. = 12 kms). The 327 municipalities surveyed were matched to their closest weather station to determine their historical precipitation for the month of May.[8]

4. Identification strategy

We exploit time and spatial variation in the trajectory and intensity of the shock across Guatemalan territory for identification in a D-D analysis. The standard assumption underlying the internal validity of our empirical strategy is that differences between the treatment and comparison groups would have remained constant in the absence of Agatha. In the following section we provide empirical evidence supporting the validity of this assumption using two waves of household data spanning a pre-shock period.

A key element of our research design is the treatment (that is, 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 the standardised precipitation anomalies in May 2010 for each weather station to identify areas that experienced extreme rainfall shocks. 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 as excessive rainfall shocks precipitation anomalies that were two or more standard deviations above the historical mean, a typical threshold used in the literature. The treatment status of households is thus coded by a binary variable (*Shock* = 1 for affected households, = 0 otherwise) according to the standardised precipitation anomaly of the closest weather station. In the robustness section, we discuss the sensitivity of the results to alternative definitions of the precipitation anomalies.

The base empirical models are estimated using the following specification:

$$Y_{imt} = \beta_0 + \beta_1 2011_t + \beta_2 \text{Shock}_m + \beta_3 (2011^{*}\text{Shock})_{mt} + X_{imt}'\gamma + \varepsilon_{imt} \quad t = 2006,\ 2011 \tag{1}$$

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 change in the welfare outcome of households across all municipalities between 2006 and 2011; $Shock_m$ is a treated municipality fixed effect that captures time-invariant systematic differences for affected villages relative to control villages. The term 2011*Shock_{mt} is a standard double-difference interaction. All regressions control for a vector of household-level characteristics X_{imt} that are expected to not be endogenous to the shock. These characteristics include age, gender, years of education, marital status and ethnicity of the household head, as well as location (urban or rural). Finally, ε_{imt} is a random, idiosyncratic error term. B_3 is the (reduced-form) parameter of interest.[9]

In order to better fit the distribution of the rainfall associated to the disaster and improve the measurement of the shock, we also estimate models that take into account the varying strength of the event. Affected households are classified into low-, medium- and high-intensity groups if the standardised precipitation anomaly in May 2010 falls between two and three, three and five, and more than five standard deviations away from the long-term mean, respectively. The specification for this treatment dose analysis is as follows:

$$Y_{imt} = \beta_0 + \beta_1 2011_t + \beta_2 \text{Shock}_m + \beta_3 L_{mt} + \beta_4 M_{mt} + \beta_5 H_{mt} + X_{imt}'\gamma + \varepsilon_{imt} \qquad (2)$$

where L_{mt}, M_{mt}, and H_{mt} are the standard double-difference binary interactions for each of the sub-treatment groups. The parameters of interest are β_3, β_4, and β_5.

Two standard deviations may be an arbitrary cutoff to accurately capture excessive (damaging) rainfall. Moreover, the occurrence and intensity of floods are also influenced by geological, topological and hydrological characteristics. In an extended specification of the empirical models, we replaced the variable *Shock* for municipality fixed effects to account for these factors. As noted below, the results also hold for this specification.

Concerns of measurement error stemming from the way that the precipitation anomalies are defined may remain. To explore this, we test the accuracy of the shock measure to predict the realisation of floods in the aftermath of Agatha reported by local authorities.[10] We run models with the probability of a municipality reporting at least one flood as the dependent variable and the standardised rainfall recorded in May 2010 and surface area of the municipality as regressors. We observed a strong and statistically significant association between the continuous shock measure and the occurrence of at least one flood in a municipality. An increase of a standard deviation above the historical rainfall mean due to Agatha was associated with an increase of 26 percentage points in the probability of a municipality reporting a flood (Table 1). A map that overlays the geo-referenced position of municipalities and floods shows a higher concentration of events in treatment municipalities (Figure A2 in the Online Appendix).

Table A1 (in the Online Appendix) presents summary statistics of baseline key demographics and socioeconomic variables – including pre-shock means of the outcome variables. Balancing tests in the top panel of the table reveal that the differences between the two groups are statistically significant for a subset of these variables. 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. The main outcome variables analysed (consumption per capita and poverty incidence) are fully balanced. In spite of that, the models are run with an array of cross-sectional time-invariant covariates to control for possible systematic differences between the two groups – including possible compositional changes over time – and to increase the precision of the estimates.

Table 1. Correlation between number of floods reported after Agatha and treatment status of the municipality

	Z-score	Area	Constant
Affected municipality (2sd)	0.026*	−0.000***	0.429***
	[0.013]	[0.000]	[0.055]

Notes: Observations: 333 municipalities. 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.

5. Empirical analysis

5.1. Results

5.1.1. Household consumption and poverty. The paper initially investigates the extent to which households hit by Agatha cut back their expenditure 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 (solid lines) (Figure 1).[11] The data show that there were not large discrepancies in the densities of the treated and comparison groups at baseline (graphs at the top) as evidenced by the little difference between the estimated densities (graphs in the second row). The story is rather different after the shock. As shown in the third row, there was a left-shifting of the density among affected urban households compared to non-affected households. In contrast, the densities for both groups of households in rural areas behaved more or less similarly. Unconditional double differences of the densities over time (shown at the bottom of Figure 1) 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 econometrically tested the observations emerging from the visual inspection of the empirical densities. Table 2 shows estimates of the D-D estimator (β_3) from Equation (1). 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 61 quetzales (7.7% with respect to its pre-shock median value) among affected households (column 1, Table 2). Results in the whole sample are driven by the impacts among urban households, for which consumption per capita declined by 12.6 per cent relative to the median at baseline. Estimates from the treatment dose specification (Equation (2)) point to similar results. Household expenditure fell across the three categorical levels of precipitation anomalies (column 2, Table 2), again more noticeably among urban households whose point estimates are in the 9–14 per cent range. 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, lending credibility to the shock measure. Overall, results from models that replace the variable *Shock* with municipality fixed effects are almost identical (not shown but available upon request).

The fall in expenditures pushed some households below the minimum consumption threshold used in Guatemala to distinguish poor from non-poor households. Linear probability models of the poverty headcount following the model defined in Equation (1) indicate that poverty increased by almost 2 percentage points or 4.4 per cent (column 3, Table 2), although the effect is not statistically significant.[12] In line with the heterogeneity of the impacts on consumption, the result is driven by a higher incidence of poverty in urban areas, where poverty rates rose by 5 percentage points (16%) (p-value = 0.026). This translates into approximately 80,000 additional families falling into poverty. Results from the treatment dose specification (Equation (2)) confirm these results for urban areas.

In trying to qualify the deterioration of household welfare in urban centers, we examine which expenditure items were more compromised. We find statistically significant evidence that food expenditures among affected households fell by around 12 per cent of the baseline level, accounting for close to 40 per cent of the total reduction in consumption (Table 3). By way of illustration, urban and rural poor households devoted 42.3 per cent and 47 per cent, respectively, of their budget to food expenditures in the baseline sample. There is no data to test whether households managed to protect calorie intake despite the lower expenditure by, for instance, substituting expensive calories with cheaper calories. Nonetheless, the existing literature on the relationship between income or expenditure and calories suggests that the effects on nutrition may not be trivial. Whereas estimates of calorie-income elasticities for developing countries vary considerably, largely for 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 & Thomas, 1995, Subramanian & Deaton, 1996). Taking this range as a reference, the effect of Agatha translates into a fall in calory consumption from 2 per cent to 5 per cent, equivalent to anywhere from 45 to 110 fewer calories per capita per day based on the representative dietary energy consumption of Guatemalans.[13]

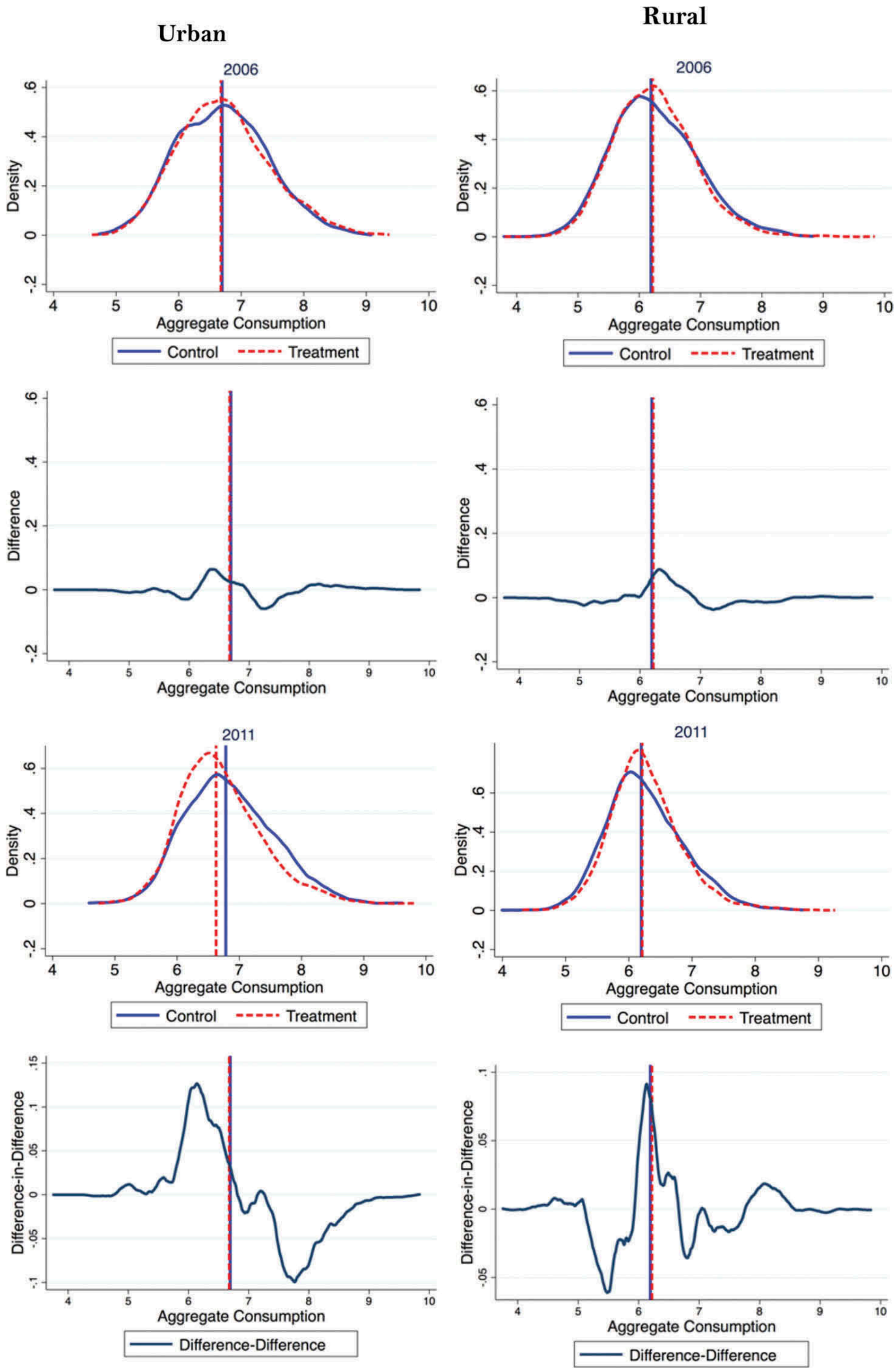

Figure 1. Pre- and post-shock density functions of household consumption per capita for treatment and control groups.
Source: Calculations by the authors based on data from Encovi (INE) and Insivumeh.

Table 2. Impacts of Storm Agatha on household consumption and poverty

	Total consumption		Poverty	
Measure of shock	(1)	(2)	(3)	(4)
Panel A: Total				
t * (rainfall z-score> 2)	−61.813**		0.019	
	[26.535]		[0.019]	
t * (2 < rainfall z-score ≤ 3)		−62.210		0.055**
		[39.055]		[0.026]
t * (3 < rainfall z-score≤ 5)		−106.093***		0.032
		[28.233]		[0.023]
t * (rainfall z-score ≥ 5)		5.606		−0.042
		[38.853]		[0.025]
Baseline Median/Mean	598.8	598.8	0.453	0.453
Panel B: Urban				
t * (rainfall z-score> 2)	−182.542***		0.050*	
	[43.382]		[0.026]	
t * (2 < rainfall z-score ≤ 3)		−139.537*		0.101***
		[78.970]		[0.039]
t * (3 < rainfall z-score≤ 5)		−259.691***		0.081***
		[44.577]		[0.030]
t * (rainfall z-score ≥ 5)		−126.811**		−0.007
		[53.364]		[0.031]
Baseline Median/Mean	796.7	796.7	0.306	0.306
Panel C: Rural				
t * (rainfall z-score> 2)	3.461		0.012	
	[33.897]		[0.026]	
t * (2 < rainfall z-score ≤ 3)		−23.095		0.034
		[37.346]		[0.031]
t * (3 < rainfall z-score≤ 5)		−5.828		0.014
		[37.330]		[0.031]
t * (rainfall z-score ≥ 5)		82.758		−0.039
		[53.535]		[0.042]
Baseline Median/Mean	496.9	496.9	0.561	0.561

Notes: Observations: 26,587 Total; 11,225 Urban; 15,362 Rural. 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 per capita of a household. Quetzales of 2006. For Total consumption the baseline median is presented. Poverty means that the per capita expenditure is under the moderate 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. Full results of the regression available in the Online Appendix.
Source: Calculations by the authors based on data from Encovi (INE) and Insivumeh.

This result is not trivial. At 43.4 per cent, 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%) (2008–2009 Maternal and Infant Health Survey).

Almost the rest of the fall in consumption among urban households is explained by a decline of nearly 80 per cent in expenditure on health services and durables, including in the latter items such as stoves or refrigerators. Urban households also cut back on education-related expenses (around 13%) although – as will be discussed below – this is not associated with an increase in dropout rates.

5.1.2. Household income and adult labour supply. We investigated if the fall in household consumption is itself the result of a negative income shock triggered by the storm. Analogous to the analysis of consumption, we ran standard D-D models using the binary treatment. The results – summarised in

Table 3. Impacts of Storm Agatha on consumption components

	Food	Health	Education	Durables
Measure of shock	(1)	(2)	(3)	(4)
Panel A: Total				
t * (rainfall z-score> 2)	−12.413	0.949	−5.693**	−14.308*
	[10.447]	[2.486]	[2.473]	[8.526]
Baseline Median	283.5	3.314	4.103	7.869
Panel B: Urban				
t * (rainfall z-score> 2)	−45.542***	−7.457*	−7.791	−49.549***
	[15.282]	[4.249]	[4.789]	[14.968]
Baseline Median	336.1	4.571	11.82	15.91
Panel C: Rural				
t * (rainfall z-score> 2)	9.361	5.805**	−3.088	−3.083
	[13.236]	[2.806]	[2.184]	[7.685]
Baseline Median	250.4	2.481	1.961	4.378

Notes: Observations: 26,587 Total; 11,225 Urban; 15,362 Rural. 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 per capita 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All consumption components used in per capita terms.
Source: Calculations by the authors based on data from Encovi (INE) and Insivumeh.

Table 4 – indicate that Agatha is associated with a reduction of income per capita in the order of 10 per cent. Unpacking the effects by income components reveals that the fall in total income is largely driven by a drop in income from labour, particularly from salaried jobs in urban areas, corresponding to 27 per cent of the baseline median (third column of Table 4). Indeed, lower wage income among affected urban households helps explain nearly 70 per cent of the total decline in household income per capita. The results further show that affected urban households attempted to cope by increasing non-labour income, as suggested by the positive and statistically significant coefficient in column 5 of Table 5. Meanwhile, none of the point estimates for income components in the rural sample are statistically significant.

There is evidence that the shock also influenced the labour supply of adults. We first investigate changes in the decision of whether to work or not (extensive margin) among adults 17–65 years old. Irrespective of the location (urban or rural) or gender of the individuals, econometric results from a linear probability model of Equation (1) give no evidence of Agatha changing labour participation rates in affected villages (Table 6). The effects happened instead on the intensive margin. Adults from affected households increased the number of hours worked in response to the shock. For the whole sample, affected adults located in affected areas worked on average two more hours per week in the aftermath of the event, amounting to an increase of 4.7 per cent relative to the baseline mean (approximately 42 hours/week). The extra labour supply is mostly driven by male workers in urban centers, who worked on average for 2.2 hours more per week (Table 5).

Finally, wages fell in tandem with the increase in the number of hours worked, possibly signaling a general equilibrium effect. Hourly wages for the whole sample fell notably among workers in shock areas by 0.5 quetzales/hour, 5.4 per cent with respect to the median hourly wage at baseline (9.2 quetzales/hour) (results also shown in Table 5). The size of the wage effects is larger for urban men workers with salaried jobs, for whom hourly wages fell by 9.3 per cent.

5.1.3. Child school participation and labour. 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,

Table 4. Impacts of Storm Agatha on income sources

	Total income	Labour income	Labour income from salary work	Non-wage income	Non-Labour income per capita	Private transfers	Public transfers	Other non-labour income
Measure of shock	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Total								
t * (rainfall z-score> 2)	−46.2*	−49.7**	−35.2**	−14.4	12.3	4.9	0.2	−6.170
	[26.8]	[22.0]	[15.4]	[12.4]	[8.9]	[5.9]	[0.9]	[11.012]
Baseline Median^ʹ	566.6	391.7	198.4	46.29	20.50	69.86	10.77	78.34
Panel B: Urban								
t * (rainfall z-score> 2)	−54.5	−55.6*	−35.9*	−19.7	34.4***	7.9	0.8	−0.3
	[39.0]	[28.8]	[18.4]	[20.7]	[12.8]	[8.7]	[0.9]	[22.6]
Baseline Median^ʹ	781.7	556.3	326.2	35.37	15.70	70.77	7.189	142.7
Panel C: Rural								
t * (rainfall z-score> 2)	−15.4	−23.2	−21.4	−1.8	7.2	5.2	−0.6	−1.9
	[28.6]	[22.6]	[16.9]	[14.0]	[9.9]	[7.4]	[1.2]	[6.0]
Baseline Median^ʹ	438.6	289	126.5	50.08	23.39	69.21	13.35	31.78

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-labour 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. All income sources used in per capita terms.
Source: Calculations by the authors based on data from Encovi (INE) and Insivumeh.

increased absenteeism of teachers and limited physical accessibility. Furthermore, as shown above, household budget constraints can be aggravated by a negative shock, reducing the demand for education, and credit constrained households may need to rely on the labour force of their children.

We investigate the possibility of Agatha prompting these two household responses. Table 6 summarises 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 7–15 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 location indicates that the reduction in school participation occurs in rural areas. The attendance rate fell by 2.7 percentage points (p-value = 0.073), equivalent to a reduction of 3.3 per cent with respect to baseline. Subgroup analysis by gender (not shown) and age groups suggest that school attendance fell for children of all ages and both genders more or less equally. Anecdotal evidence from national authorities suggests that schools facilities in some rural areas, as well as physical access to them, were heavily affected by Agatha.

The results also reveal an increase in child labour 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 (for example domestic chores, child caring and so on). Requiring children to work can also be a mechanism for adults to free up time and further increase their own labour supply. Results show that children 7–15 years old in affected areas were 3.1 percentage points (10.8%) more likely to engage in paid and non-paid activities (Table 6). In line with the geographic concentration of the negative impacts on school attendance, the effects on labour force participation are driven by households in rural villages hit by Agatha. Child labour increased by 4.2 percentage points or 12.8 per cent of the pre-shock level among these households, mostly among boys 12 and 15 years old.

Table 5. Impacts of Storm Agatha on labour supply and hourly wages

	Working	Hours worked	Hourly wage
Sub-groups	(1)	(2)	(3)
Panel A: Total			
Total	0.001	0.891	−0.475**
	[0.006]	[0.710]	[0.240]
Men	−0.002	0.893	−0.626**
	[0.005]	[0.711]	[0.290]
Women	0.011	1.190	−0.127
	[0.013]	[0.997]	[0.301]
Panel B: Urban			
Total	0.003	2.008**	−0.906***
	[0.012]	[0.862]	[0.319]
Men	0.002	2.265**	−1.083**
	[0.011]	[0.927]	[0.436]
Women	0.005	1.968	−0.647
	[0.015]	[1.223]	[0.494]
Panel C: Rural			
Total	−0.005	0.207	−0.065
	[0.007]	[0.931]	[0.287]
Men	−0.002	0.395	−0.217
	[0.005]	[0.921]	[0.328]
Women	−0.002	0.182	0.380
	[0.018]	[1.457]	[0.399]

Observations: 55,194 Total; 23,323 Urban; 31,871 Rural. 58 per cent are men. 23 per cent do not report wage.
Notes: Results from diff-diff regression on the sample of all adults 17–65 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 4 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.

In order to check whether the extra child labour supply in the extensive margin 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. The outcome variable in this case 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 labour force participation attributed to Agatha is mostly seen among rural children – predominantly boys – who also stopped attending school (Table 6). In contrast, the proportion of children simultaneously working – or looking for a job – and attending school did not change, providing an indication that at the margin the added labour force of children reduced their school participation.

5.2. *Robustness analysis*

Several empirical checks confirm the robustness of the findings. We first test the central assumption underlying the internal validity of the identification strategy, namely that the outcomes for affected and less- or non-affected households would not have followed systematically different pathways in the absence of the shock. To do so, we pool two rounds of the *Encovi* data collected before the shock (2000 and 2006) to estimate placebo treatment effects of a 'fake' shock on consumption and poverty. Overall, the results do not provide evidence of diverging trajectories preceding the shock between the treatment and control groups (Table 7, panel A). The double-difference estimators for consumption per capita and poverty headcount are statistically insignificant.

Table 6. Impacts on children's schooling and labour force participation

	School attendance			Labour force participation		
	715	711	12 15	7 15	7–11	12–15
National	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Total						
t * (rainfall z-score> 2)	−0.019*	−0.025**	−0.014	0.040**	0.027*	0.058**
	[0.011]	[0.012]	[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)	0.008	0.011	0.004	−0.009	−0.018	0.001
	[0.016]	[0.015]	[0.028]	[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**	−0.020	0.053**	0.039*	0.073**
	[0.015]	[0.014]	[0.022]	[0.023]	[0.021]	[0.032]
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.

In a second exercise we test for other possible forms of sample selection in our data. Using pre- and post-shock data from 2006 and 2011, we run models to estimate placebo treatment effects on variables measuring household head characteristics assumed to not be directly affected by the shock (age, education, gender, marital status or area of residence). Nonetheless, results of this placebo test show that Storm Agatha has no statistically significant relationship with any of these variables, ruling out possible compositional changes due to endogenous migration or mortality (Table 7, panel B).

To further rule out concerns over sample selection produced by endogenous migration, we run econometric models of a binary variable that identifies households that moved to another Guatemalan municipality after Agatha occurred against measures of the shock and a subset of covariates.[14] 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 fewer) households to migrate (Table 7, panel C).

A potential concern is the possibility of a systematic – as opposed to random – measurement error in the shock variable. For instance, our empirical models may be picking up the cumulative effects of other rainfall shocks that occurred in the past if their geographic location overlap closely with Agatha's path. To investigate this, we checked if rainfall variability – including the occurrence and frequency of extreme events – in a long pre-Agatha period (1970–2009) differed systematically between 'affected' and 'less- and non-affected' areas. We computed the coefficient of variation to account for underlying differences in the probability distribution of precipitation between the two areas. This normalised measure of dispersion shows that rainfall variability is comparable between treated (1.17) and control municipalities (1.12). Likewise, the spatial location of precipitation anomalies caused by the three strongest events that hit Guatemala in the 2000s (Hurricane Stan 2005, Storm Barbara 2008 and Hurricane Mitch 2008) does not overlap with the path of Agatha. Also, spatial analysis of the geographic position of rainfall stations does not suggest that they are systematically situated in regions where underlying rainfall is higher or where the readings are likely to be more accurate.

Table 7. ‘Fake’ treatment effects (Panels A and B) and migration analysis (Panel C)

	Total consumption	Health	Education	Moderate poverty	Extreme poverty
Measure of shock	(1)	(2)	(3)	(4)	(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					
	Education	Age	Gender	Area of residence	Single-married
Measure of shock	(1)	(2)	(3)	(4)	(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					
	HH Head moved less than 1 year ago/Born in different municipality			HH Head and spouse moved less than 1 year ago/Born in different municipality	
Measure of shock	(1)			(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.

Additional bias in measurement could arise if historical rainfall and precipitation anomalies are wrongly matched to municipalities. Due to the low density of stations in some parts of the country, a small subset of municipalities was paired with stations that may be too far away to accurately track rainfall patterns. The closest weather station for nearly 4 per cent of households lies more than 50 kilometers away. We performed sensitivity tests running the consumption and poverty models in a restricted sample using the rest of the households (96%). The negative effects on consumption and the associated increase in poverty not only held in this subsample, but they were also more precisely estimated, as reflected by the lower standard errors (Table A3 in the Online Appendix).

Finally, the results are also robust to definitions of the shock that rely on different critical thresholds (that is, 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). Similarly, results also hold when the main empirical models are re-estimated drawing from a larger balanced panel of weather stations used to determine historical rainfall over the period 1990–2011.[15]

5.3. Interpretation

In line with most of the existing evidence, the findings of this paper highlight that the wellbeing of households is sensitive to the consequences of weather-related disasters (Hoddinott 2006; Hoddinott and Kinsey, 2001; Maccini and Yang, 2009). However, the results depart from existing research by documenting that, relative to rural households, urban families appear to have carried the heaviest burden – at least in terms of household consumption and poverty. Why urban households were disproportionally affected is an important question. Data limitations make it difficult empirically to disentangle the mechanisms driving the impacts. Yet, in what follows we posit some informed hypotheses about the possible leading channels.

The first observation pertains to 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 standardised 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 across areas. Figure A3 (in the Online Appendix) plots the density of the z-scores for affected households by area. Close to 40 per cent of the households in urban centres recorded precipitation 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 z-scores >6 relative to those with 2<z-scores ≤ 6. The results suggest that the magnitude of the shock is associated with the spatial concentration and size of the impacts (Table A4 in the Online Appendix). 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 price rises, which were likely influenced by market disruption following the disaster. Anecdotal assessment of the disaster suggests that the major damage to basic economic infrastructure and systems was registered in urban centres. We 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 Storm Agatha. The cumulative increase in food prices 10 months after the shock was 17 per cent. Even though not fully conclusive, breaking the data down by the lowest level of disaggregation (eight geographic areas[16]) is suggestive of higher price increases and volatility consistent with the geographic path of the storm (Figure 2). In regions such as *Sur Oriente* and *Noroccidente*, where nearly two-thirds of the households were affected, food prices increased by 65 and 20 per cent, respectively. To further investigate price channels, 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 this price data as the response variable in a D-D framework shows steep statistically significant price increases in treated urban areas for basic foodstuffs, such as milk (27%), sugar (16%), meat (8%) and beans (6%). In contrast, prices appear much more stable in rural areas (Figure 3).

The lower sensitivity of rural households to the negative effects of Agatha may be partly explained by the 'favourable' timing of the storm with respect to local agricultural cycles. We used the 2003 Agricultural Census from the Ministry of Agriculture to map the main crops grown in affected areas at baseline. Around 72 per cent of the land cultivated corresponds to maize, beans, coffee and sugar cane. The typical annual cycle of planting, growth and harvest of these four crops in Guatemala is shown in Table A5 (in the Online Appendix). The rainfall caused by Agatha occurred in late May, right in the middle of the seeding period of maize and beans, possibly mitigating the decrease in yields commonly caused by water deficits during the flowering period. Similarly, the excessive precipitation fell well outside the traditional coffee and sugar harvesting seasons. Using data from *Faostat* (FAO), we construct indices to track the annual production of these four crops in Guatemala during the period 2006–2012. Except for a slight decline in the production of sugar cane after Agatha, there is not a large drop in the annual yields of any of the four crops for the interval between the shock and the reference

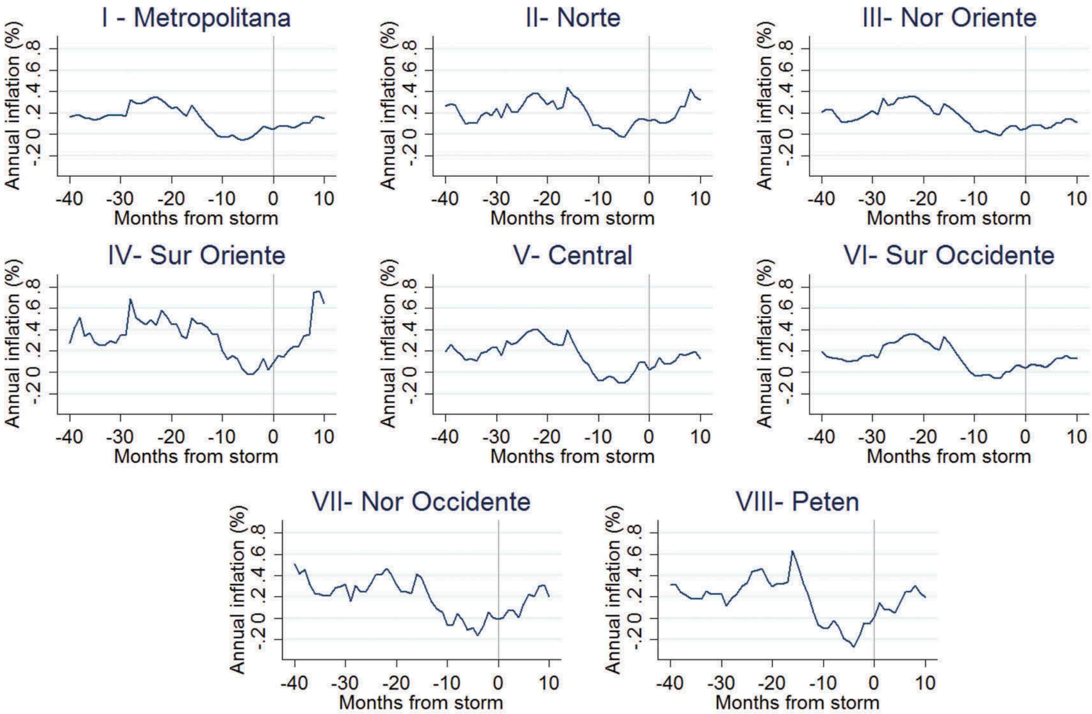

Figure 2. Food price index by geographical regions.
Notes: Vertical line denotes the timing of the shock.
Source: Calculations by the authors based on price indices by INE.

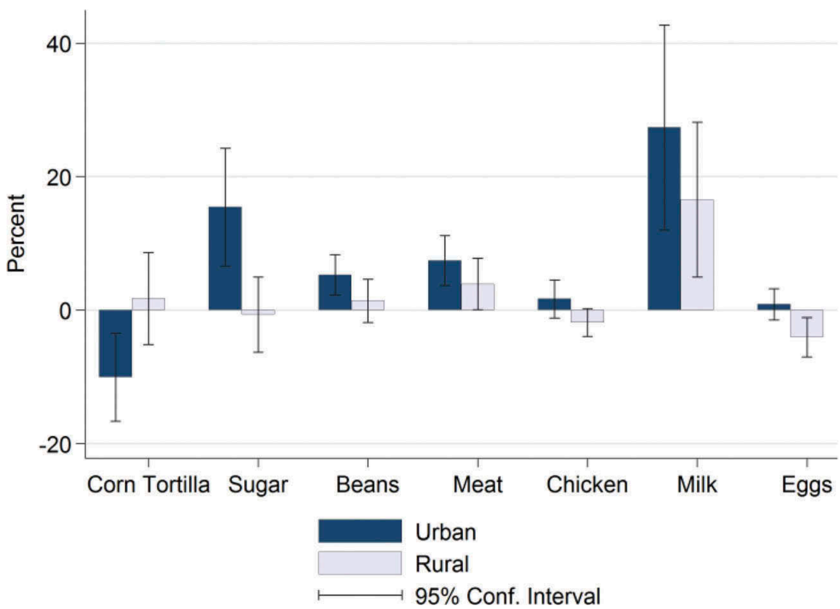

Figure 3. Treatment effects on the prices of selected food items.
Notes: Point estimates from econometric regressions specified as models in Table 1. Robust standard errors clustered at the municipality level.
Source: Calculations by the authors based on data from Encovi (INE)

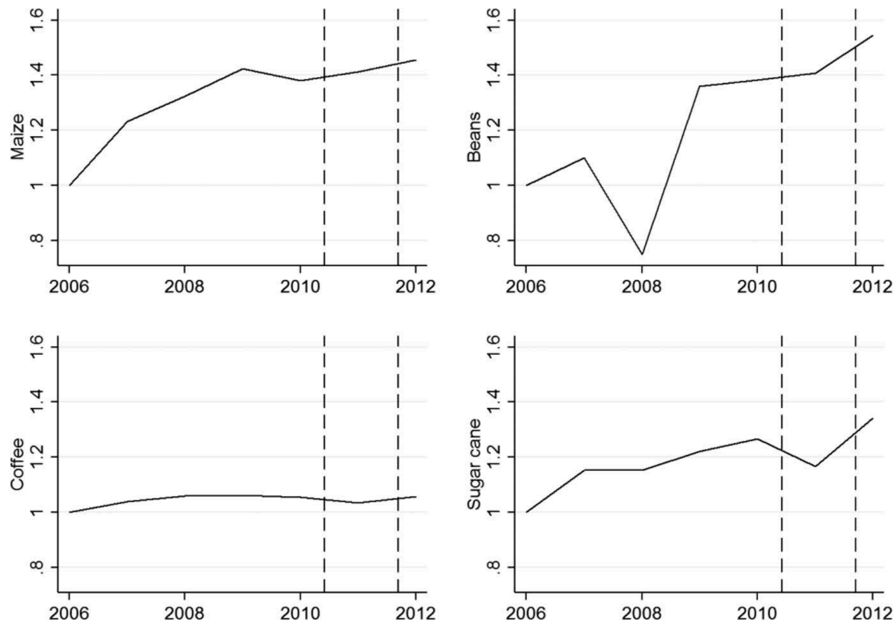

Figure 4. Agricultural output of four main cash crops in areas affected by Storm Agatha (2006–2012).
Notes: Dotted line denotes the interval of time covered in the analysis.
Source: Calculations by the authors based on data from Faostats (FAO).

period covered by the *Encovi* survey (shown by the dotted vertical lines in Figure 4), ruling out supply shocks.

Finally, social protection policy could have played a role in partly shielding the basic welfare of rural families. In April, 2008, the Government of Guatemala began implementing a standard Conditional Cash Transfer (CCT) programme, known as *Mi Familia Progresa*. The programme transfers money to families living in extreme poverty that have children aged 0–15 years and/or pregnant women. The vast majority of programme beneficiaries are rural households.[17] At the time of Agatha, the CCT programme covered nearly 800,000 families, many of them located in severely stricken parts of the country. The cash transfers could have contributed to smooth basic consumption. Yet, the weak monitoring and enforcement of the school attendance conditionality – as reported by programme managers – did not prevent some children from missing school. More analysis is however necessary to sign the net effect from the interaction between participation in the CCT programme and the shock.

6. Conclusions

This paper provides robust evidence that a major tropical storm that hit Guatemala in 2010 led to a sizable deterioration of human welfare among affected households. On average, per capita consumption fell by 8.2 per cent relative to the median at baseline. While negative impacts triggered by excessive rainfall have been documented in the literature, most studies have shown that rural households are often disproportionally affected. Contrary to this, our work finds that urban households can be equally or even more vulnerable. They saw their consumption per capita fall by 12.6 per cent

The negative effects of the shock span other areas of human welfare. The incidence of poverty in urban areas increased by 5.5 percentage points, equivalent to 18 per cent with respect to the poverty headcount at baseline. Affected households cut back on food expenditure by 10 per cent, equivalent to a reduction of over 100 calories per day per household member. We also find evidence that households reduced expenditure 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 in the order of 10 per cent, driven mostly by a drop of labour income among urban salaried jobs. To cope with the shock, male adults adjusted on the intensive margin by increasing the number of hours worked (1.9 hours, or 3.7%, more per week). This additional labour supply occurred in tandem with a fall in the remuneration of workers, possibly signalling a sort of general equilibrium effect.

A leading factor driving impact heterogeneity across areas is the strength of the shock itself. Studies often fail to quantify the intensity of natural shocks or map such intensity variation to the units of analysis. We show that part of the reason as to why the negative effects were concentrated among urban households pertains to the fact that excessive precipitation was stronger in urban areas. There is also suggestive evidence that food prices increased after the shock in the urban areas that saw the largest precipitation anomalies, which may have been associated with the destruction of infrastructure and disruption of markets.

At the same time, the lower sensitivity of rural households to the shock may be partly explained by the timing of Agatha in relation to agricultural cycles. For the most part, the excessive precipitation fortuitously 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. Moreover, households in rural areas may have relied on children's labour to cope with the shock. We found a sizable increase of 3.1 percentage points (10.8%) in child labour force participation in rural areas. Simultaneous to relying more on their labour force, households were also more likely to withdraw them from school, raising the risk that they drop out.

A number of checks confirm the robustness of the findings with regard to the parallel trajectories of the outcomes preceding the shock between the treatment and control groups. The results are also fairly robust to possible issues of endogenous compositional changes, non-random migration, measurement error in the shock variable, different precipitation thresholds and alternative household-to-weather station matching criteria. Importantly, the robustness checks and the gradient between the intensity of the shock and the size of the impacts support the assumption that the geographic location of the excessive rainfall due to Agatha did not overlap with the effects of the global crisis, the coverage of the CCT in rural areas or the path of previous storms.

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 per cent to 53.7 per cent (mostly in urban centres) between 2006 and 2011. Government officials and most analysts attributed this increase to the collateral effects of the 2008–2009 global financial crisis. We, however, argue that this is only part of the story. Since a large fraction of households were bunched directly above the poverty line before the shock, the fall in consumption per capita was enough to push nearly 80,000 additional families into poverty. Hence, this natural disaster is one of the key explanatory factors behind the increase in poverty. Ignoring the detrimental consequences of natural disasters on human welfare will limit the effectiveness of development policy and, in particular, of anti-poverty strategies.

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Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. It is estimated that 83 per cent of Guatemala's GDP is generated in areas especially prone to natural disasters.
2. Guatemala is administratively divided into eight regions and 22 states.
3. The 2002 census comprised 15,511 primary sampling units (PSUs) corresponding to 2,127,915 occupied dwellings. The sample for the survey consisted of 1184 (2006) and 1200 (2011) PSUs – selected from random clusters of the 2002 Census – and 14,400 dwelling or secondary sampling units (SSUs), selected randomly within the cluster. The PSUs overlap in 2006 and 2011.
4. Household expenditure captured in the survey include expenses for food, rent, durable goods, payment of basic services and education, and health services. Unit prices used to value the official consumption basket that determines the poverty threshold were obtained from the household questionnaire. A consumption price index was 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 unified the methodologies by applying the 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: nine 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 bracket 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.
6. Daily rainfall and temperature data are patchy across stations in the registry so we used 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 (that is, 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 one km.
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 (for example, a flood) as well as whether the event was caused by Agatha. These data have two caveats. They include only those events reported by local authorities – possibly missing some floods in a non-random fashion – and do not say anything about the intensity of the floods
11. Expenditure includes 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 labour supply).
12. Compared to the consumption models, the analysis of poverty requires stronger statistical power because only households crossing the poverty threshold provide variation useful to identify β_1 (Equation (1)) andβ_2, $\beta_3$and β_4 (Equation (2)).
13. The daily dietary energy consumption per capita in Guatemala is estimated at 2170 calories. Food and Agriculture Organisation of the United Nations, February 2009, 'Compendium of food and agriculture indicators – 2006'.
14. It is worth noting that the *Encovi* surveys only track domestic migration.
15. These results are not shown in the paper but are available from the authors upon request.
16. Price data in Guatemala does not allow for discrimination between urban and rural areas.
17. There is also a fraction of programme participants from marginal areas in the peripheries of urban centres.

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