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Hurricane Mitch and consumption growth of Nicaraguan agricultural households

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Abstract

Risk has been presented as a cause of poverty persistence under imperfect insurance mechanisms. This paper assesses the ex post effect of hurricane Mitch on consumption growth of Nicaraguan agricultural households. How persistent was Mitch's direct impact beyond October 1998 damage? A nationally representative panel is available for 1998 and 2001, but affected households were also re-surveyed in 1999. Given the data design, idiosyncratic and common dimensions of the shock can be disentangled, together with its short and medium-term impacts. Satellite rainfall observations are interpolated at municipal centres to complement survey reports of hurricane-induced losses. Within the treated sample, micro-growth model estimates only point to a limited short-term negative impact of idiosyncratic damage, at most through floods and displacement. Mitch's medium-term common impact is considered in an experimental set-up. Households affected by Mitch do not suffer from lower growth between 1998 and 2001, even accounting for spatial heterogeneity. Overall, hurricane Mitch's direct consumption impact thus exhibits little persistence.

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1 Introduction

Rationalising poverty persistence requires a structural understanding of poverty mechanics in a dynamic world. Given the limitations of formal and informal insurance mechanisms in the uncertain environment where much of the poor live, risk has been singled out not only as a dimension of poverty, but crucially as a cause of low long-term welfare levels (Dercon, 2004). Linking risk to poverty persistence yields intrinsically dynamic statements. With growing panel data, explicit analysis of households' welfare dynamics at the micro-level are multiplying[1], and the dynamic impact of shocks on welfare changes can be assessed (Dercon, 2005). This paper evaluates the impact of hurricane Mitch on consumption growth of Nicaraguan agricultural households by contrasting its idiosyncratic and common effects in the short and medium terms. Since insurance mechanisms rarely deal effectively with common shocks such as the one embodied by Mitch (Ehrlich and Becker, 1972), the context is appealing to test the link between shocks and welfare dynamics.

Mitch's intense rainfall caused extensive damage in Central America in October 1998 (ECLAC, 2000). Nicaraguan data have engaging features to study the persistence of Mitch's direct consumption impact. The National Institute for Statistics and Census (INEC) collected three Living Standards Measurement Surveys (LSMS): nationally representative LSMS are available in 1998 and 2001, but households located in communities affected by Mitch were also revisited in 1999. The persistence of the shock can thus be assessed in two complementary ways. First, the impact of idiosyncratic hurricane losses is analysed within the 1998-1999-2001 panel of affected households. The focus is on the effect of variations in relative losses on short-term consumption growth. An empirical growth model is used as evaluation tool and estimated using dynamic panel data methods. Second, the medium-term persistence of Mitch's common impact is tested in an experimental set-up. Household consumption in treatment and control groups is contrasted for the 1998-2001 period based on difference-in-differences estimates. Complementary measures of the hurricane's incidence are used throughout the analysis. Self-reported losses are obtained directly from the 1999 LSMS. In addition, innovative satellite-based rainfall data from NASA tropical rainfall measurement project (TRMM) are interpolated at municipal centres to provide an exogenous measure of the common dimension of the shock.

The literature on natural disasters is often limited to determination of victims' profiles or direct damage assessment (ECLAC, 2000; Morris et al., 2002). The channels through which estimated losses shape welfare dynamics at the micro-level are rarely analysed. Two recent papers on hurricane Mitch constitute important exceptions. Baez and Santos (2007) identify a disproportionate adverse medium-run effects on children's well-being by focusing on health, nutrition and labour force outcomes. Carter et al. (2007) study the impact of

[1] For instance, Baulch and Hoddinot, 2000; Lokshin and Ravallion, 2000; Jalan and Ravallion, 1998, 2002, 2004.

the hurricane on Honduran households' asset trajectories and show that "the effects of the hurricane on assets were of longer duration and felt much more acutely" for the lowest wealth group (p.852). While these recent contributions focus on indirect mechanisms that might affect welfare in the longer term, this paper tackles the direct effect of the shock on consumption.

The main results can be detailed in the following way. Within the treated sample, estimates point to a limited short-term negative impact of idiosyncratic damage, at most through floods and households' displacement, not rainfall or self-reported losses. In the medium term, difference-in-differences estimates reveal that Mitch did not aggravate the consumption differential between control and treatment groups. There is evidence of higher growth for control communities in municipalities hit by the hurricane. Such spatial heterogeneity stems from differences at both the household and municipality levels, but remains insufficient to explain the hurricane's absence of negative effect. Mitch's direct welfare impact is therefore characterised by a lack of persistence. In the end, the overall picture that emerges is that the link between the hurricane shock and welfare outcomes is indirect and likely to unfold in the long-term cost of mitigating mechanisms such as those suggested by Baez and Santos (2007) or Carter et al. (2007).

The structure of the paper is as follows. Section 2 describes the data (self-reported losses, satellite rainfall measures and welfare patterns). Section 3 uses a micro-growth model to evaluate the short-term effect of variations in hurricane-induced damage within the sample of affected households. Section 4 assesses the medium-term common impact of Mitch by contrasting consumption growth of control and treatment groups. Section 5 concludes. The appendix contains tables and figures.

2 Data

2.1 Nicaraguan LSMS

INEC collected three LSMS in panel in 1998, 1999 and 2001. 1998 and 2001 LSMS are nationally representative. Hurricane Mitch struck Central America at the end of October 1998, shortly after completion of the 1998 LSMS. In 1999, INEC re-surveyed households located in communities judged affected by the hurricane[2]. 1999 data is not representative of the country nor of the population affected by Mitch, but its availability in conjunction to 1998 and 2001 nationally representative surveys remains of the highest appeal. Treatment and control groups can be formed from the 1999 LSMS and Mitch can be studied as a natural experiment using the 1998-2001 panel. In parallel, the 1998-1999-2001 panel allows performing an evaluation of Mitch's relative impact within the treated sample. The 1998-2001 and 1998-1999-2001 panels will therefore constitute the basis for two complementary steps of the analysis. The short-term and

[2] Criteria for inclusion of households in 1999 LSMS are discussed in section 4.

medium-term impacts of the shock can be disentangled, while its idiosyncratic and common dimensions can also be contrasted.

Overall, the 1998-2001 spell is one of limited welfare improvement in Nicaragua. Both general and extreme poverty decrease in the nationally representative samples (from 44.4% to 40.8%, respectively 19.9% to 13.2%). This paper focuses on agricultural households for whom detailed hurricane losses are available and growth models can potentially apply. The 1998-1999-2001 panel contains consumption and shock data for 197 agricultural households, and the 1998-2001 panel for 1016 agricultural households[3]. Table (1) displays key descriptive statistics for consumption[4] and poverty[5]. Since poverty is predominantly rural in Nicaragua (World Bank 2001, 2003), poor households are over-represented in the agricultural panels. In the Mitch panel, 74.1% of households are poor and 32% extremely poor at the baseline.

While the 1998-2001 agricultural panel echoes national welfare trends in terms of poverty reduction, average consumption growth remains negative. Patterns are also mixed in the Mitch panel. General poverty decreases in both spells, but extreme poverty increases in 1998-1999. In addition, average consumption growth is higher in 1998-1999 than in 1999-2001. Consumption is particularly variable in 1999. There are also large variations in growth rates but they are symmetric: some households suffer large consumption decrease between 1998 and 1999, but others enjoy large consumption growth during the same period. No large aggregate impact of hurricane Mitch on consumption therefore appears from descriptive statistics. Welfare changes exhibit substantial heterogeneity. Section 3 will analyse whether households' diverse welfare experiences are explained by variations in the hurricane-induced losses they suffered.

2.2 Self-reported hurricane damage

1999 LSMS contains self-reported hurricane-induced losses for the 197 agricultural households of the Mitch panel. Damage covers output, assets and housing. Losses are described in table (2). Capital losses affect 29% of households in the sample, averaging 1182 cordobas per household[6]. Livestock[7] constitutes an important component of households' assets. 64% of households lost livestock (mainly cattle), the average damage amounting to 1978 cordobas. Asset losses

[3] The final panels are formed of households involved in agriculture in all rounds. In the Mitch panel, 13% of 1998 agricultural households are not active in agriculture in 2001 (22% in the 1998-2001 panel). Estimations were replicated on the panel of households initially active in agriculture and results remain unaffected. Attrition will be discussed in section 3.4.

[4] This paper presents estimations for the consumption aggregate, but results are robust if the aggregate is restricted to basic goods or food consumption.

[5] Castro-Leal and Sobrado (2001), Sobrado (2001) and Sobrado (2003) detail the construction of the consumption aggregate. Consumption is expressed per capita in 1998 prices and corrected for geographical price variations. Extreme and general poverty lines respectively amount to 2489 and 4223 cordobas in 1998 (Castro-Leal and Sobrado, 2001; Sobrado, 2003). The cordoba-dollar exchange rate averaged 10.58 in 1998.

[6] Capital includes agricultural property, agricultural equipment, agricultural installations, tools and work animals.

[7] Cattle, pigs, poultry, horse and other animals.

aggregate both capital and livestock, affecting 72% of household and averaging 3160 cordobas. Losses of output are made of cultivated crops and sowing[8]. Output losses are more frequent than capital losses. In total, 94% of households suffered from output losses, averaging 5211 cordobas.

Aggregation of the asset and output dimensions of the shock yield a total measure of hurricane-induced losses[9]. 96% of households in the sample suffer from hurricane Mitch, which reflect the fact that households were re-surveyed precisely because they were located in communities affected by the hurricane. Average losses amount to 8371 cordobas in the sample, which is of large magnitude compared to average baseline consumption of a household member (3600 cordobas, table(1)). Both output and asset losses are substantial, but the former slightly larger. Incidence is also asymmetric and output losses more common: 190 households suffer from output losses, 141 from asset losses.

In addition to output and productive asset losses, the hurricane caused widespread housing damage[10](table (2)). 10% of households were permanently displaced, and 24% temporarily displaced. On the whole, losses and damage induced by hurricane Mitch therefore appear large for agricultural households, but significant heterogeneity remains in both magnitude and incidence patterns. The econometric section will test whether direct damage translate to subsequent welfare losses, and whether relative magnitude of losses explain the heterogeneity of welfare outcomes described above. It will also test for differentiated impacts across dimensions of the shock.

2.3 Satellite rainfall data

Since survey-based hurricane losses can suffer from report bias, a complementary exogenous measure of the shock is appealing. Mitch's track did not enter the Nicaraguan territory and intensive rainfall constituted the principal cause of damage (INETER, 1998; Hellin et al., 1999). Gauge data are particularly unreliable during extreme events (Hellin et al., 1999) and sparsely available in Nicaragua. Innovative satellite rainfall data are used instead. NASA's tropical rainfall measurement mission (TRMM) provides satellite monthly accumulated rainfall starting in 1998. The shortness of TRMM series is by far outweighed by its sharp geographical coverage: rainfall observations are available on a grid of 0.25 degrees of longitude by 0.25 degrees of latitude. TRMM satellite rainfall data therefore have ideal characteristics for use in conjunction with household surveys of national coverage. To my knowledge, no other paper has used TRMM data in the economic literature[11]. Bilinear interpolation is used to de-

[8] Both the incidence and aggregate value of sowing losses are much higher than cultivated crop losses.

[9] Adding a flow to a stock is of limited interest, but nevertheless gives an indication of total losses. Both measures will also be considered separately in econometric analysis.

[10] A housing damage index is built by adding values of 0 (no), 1 (limited) and 2 (serious) for damage to dwelling's roof, floor, walls and water system.

[11] Miguel et al. (2004) use satellite rainfall data from the Global Precipitation Climatology Project (GPCP). GPCP series is longer but 10 times less precise than TRMM data.

rive municipal rainfall for each set of municipal coordinates within the grid (see appendix). Figure (3) presents average municipal monthly rainfall as interpolated from TRMM. Extraordinary rainfall due to hurricane Mitch are striking in October 1998. Average rainfall amount to 539mm for agricultural households in the Mitch panel, an excess of 353mm.

Most shock measures are positively correlated, but significant complementarity remains. For instance, correlation coefficients between rainfall and monetary losses are typically in the 0.1-0.2 range. In addition to rainfall, local geographical idiosyncrasies such as steepness of slopes or proximity to rivers can also explain the heterogeneous impact of the shock. This reflects heterogeneity of the shock's direct impact at the local level, as will be further discussed in the experimental section.

3 Mitch's short-term idiosyncratic impact

3.1 Micro-growth models

Empirical growth models constitute a standard tool to analyse factors of change at the micro-level. They trace back to consistent theoretical frameworks. A broad range of growth models can be translated to the micro-level, including endogenous growth through externalities (Jalan and Ravallion, 2002), but restrictive assumptions need to be imposed. Absence of within-country capital mobility is crucially required for neo-classical models to carry through. Ravallion (2005) assumes in typical fashion "an intertemporally additive utility integral, with common preferences" (p. 141), in addition to a concave household production function. Micro-growth regressions can be directly derived from such theoretical models under additional assumptions: "to derive a parametric model, one can assume constant discount rate and time preference rates" (Ravallion, 2005, p. 141).

Shocks can be built into theoretical micro-growth models. Elbers et al. (2003) develop an integrated framework to analyse households' consumption growth in presence of risk in a stochastic Ramsey model. They disentangle the ex ante and ex post effects of risk on welfare, and incorporate both output and asset shocks. In turn, Dercon (2005) models shocks into empirical micro-growth frameworks consistently with theory.

In this paper, micro-growth models are used as empirical tools to evaluate the ex post impact of hurricane Mitch for agricultural households. Still, testable hypotheses can in first approximation be seen as derived from a standard neoclassical framework where households are considered non-responsive. The ex post focus is justified by the rare occurrence of extreme events such as hurricanes in Central America. In deterministic models, the impact of shocks on welfare can be analysed through transitional dynamics: while the shock can have a positive impact on growth during the recovery spell, it has a negative impact on growth as measured from pre-shock consumption levels. Below, an empirical growth model is used to estimate the impact of the hurricane shock on

consumption growth, allowing for differentiated effects of each dimension of the shock. The next sections focus on the sample of affected households, but section 4 illustrates that difference-in-differences estimators intrinsically represent growth equations. In this sense, empirical growth models constitute a natural dynamic evaluation tool (Jalan and Ravallion, 1998)[12].

3.2 Benchmark specification

This section analyses the impact of idiosyncratic hurricane losses on contemporaneous consumption growth of treated households forming the Mitch agricultural panel. The focus is on identifying whether variations in magnitude of losses affect short-term growth and explain the heterogeneous welfare outcomes discussed in section 2.1. An empirical micro-growth model is estimated for the 197 agricultural households of the Mitch panel. The basic specification is as follows:

$$[\ln(c_{i,t}) - \ln(c_{i,t-1})] = \alpha + \beta \ln(c_{i,t-1}) + \gamma MITCH_{i,t} + \delta X_{i,t} + \upsilon_{i,t} + \eta_i \quad (1)$$

The aim is to test the impact of variations in hurricane losses ($MITCH_{i,t}$) on contemporaneous consumption growth (in particular, $\gamma < 0$), allowing for differentiated impacts of the various dimensions of the shock. Since initial consumption is measured before the shock, a negative coefficient should be expected even if households are in a recovery phase. Importantly, γ captures the impact of the shock net of mitigation strategies. Satellite municipal rainfall and self-reported measures of losses are used as alternative shock variables. These variables are equal to 0 for the 1999-2001 period. Variations in consumption growth between the hurricane and post-hurricane rounds are used to identity the effect of the shock, as will be detailed in section 3.3.

The following control variables are included. Lagged consumption ($ln(c_{i,t-1})$) serves as control for household's initial position[13]. The implications of this choice for estimation will be further discussed below. Agricultural households report whether they were affected by drought, pest, floods, or other shocks over the last year. Shock incidence dummies are constructed for each categories, and differences between rounds controlled for. Education per adult captures the number of years to achieve the highest grade for the most educated household member. Demographic controls comprise household's head age and sex, as well as changes in the number of children and adults (separately for male and female) in the household between rounds. Descriptive statistics for control variables are displayed in table (3).

Benchmark pooled OLS estimates of equation (1) are presented in table (4). No negative impact of Mitch-induced damage on consumption growth is iden-

[12] A pragmatic reason why the analysis focuses on consumption growth is that comprehensive income aggregates cannot be built from 1999 LSMS.

[13] Consumption data are more widely available than assets data. Also, assets are typically hard to value and aggregate. Results are robust to specification choice, as discussed in section 3.4.

tified: none of the hurricane shock variables is significant, although the flood dummy is only marginally insignificant. The coefficient of lag consumption is equal to -0.47. Some authors find coefficients of large magnitude (Jalan & Ravallion, 2004), but $\hat{\beta}$ reflects large consumption variability in the Mitch sample. $\hat{\beta}$ are not interpreted as convergence coefficients here, but constitute a useful indicator of the validity of the estimated model.

3.3 First-differenced estimates

OLS estimates only serve as a benchmark. In absence of repeated hurricanes and of a control group for all three rounds, the identification of the impact of the shock relies on inter-annual variations between hurricane and non-hurricane years. First-difference transformations exploit such time variation and correct for households' time-invariant heterogeneity[14] (η_i). The difference in growth rates between the two spells is used to identify the impact of the hurricane:

$$\begin{aligned}[\ln(c_{i,t}) - \ln(c_{i,t-1})] - [\ln(c_{i,t-1}) - \ln(c_{i,t-2})] = \beta[\ln(c_{i,t-1}) - \ln(c_{i,t-2})] \\ + \gamma[MITCH_{i,t} - MITCH_{i,t-1}] + \delta[X_{i,t} - X_{i,t-1}] + [\upsilon_{i,t} - \upsilon_{i,t-1}]\end{aligned} \tag{2}$$

Shock variables are equal to 0 for the 1999-2001 period. Consistent estimation relies on absence of lasting negative effects of the shock in the medium term, which will be confirmed below. Another key issue is that the strict exogeneity assumption on which classical panel data estimation builds is violated in dynamic models (Nickell, 1981). Simple first-difference estimation of equation (2) suffers from a downward bias. The dynamic panel data literature mainly focuses on the impact of the Nickell bias on the convergence coefficient (Kiviet, 1995; Judson and Owen, 1999). Crucially, Nickell (1981) stresses that coefficients of other explanatory variables can also be biased: not only is β underestimated, but first-difference estimates of γ are also inconsistent. For instance, all estimated coefficients from first-difference equations (not presented) are strongly negative and coefficients of initial consumption are equal to -1.42. Another result related to the Nickell (1981) bias is that OLS estimates are biased upwards (Bond, 2002). Although β should therefore be large in absolute value[15], coefficients smaller than -1 are of nonsensical magnitude and constitute a clear indication of the presence of a downward Nickell-type bias. Correction for Nickell bias is therefore crucial for consistent identification of the impact of the shock in equation (2).

The traditional response to the Nickell bias is to use past observations to instrument lagged value of the dependent variable (Anderson and Hsiao, 1982; Arellano and Bond, 1991). Consistent estimates can be obtained using 2SLS

[14] Random-effect models could unambiguously be discarded. Correlation between unobserved heterogeneity and control variables create a bias in OLS estimates above.

[15] A consistent estimate of the initial consumption coefficient should lie below the pooled OLS estimates (-0.47, see table(4)).

with instrumental variables that are both uncorrelated with the lagged dependent variables and orthogonal to the error terms, under predetermined initial conditions (Bond, 2002). In the present context, $\ln(c_{t-2})$ is a valid instrument under non-autocorrelation of errors and predetermination of initial conditions. With three time-series observations, Arellano and Bond (1991) GMM estimator collapses to the exactly identified Anderson and Hsiao (1982) estimator: $\ln(c_{i,t-2})$ serves as instrument for $[\ln(c_{i,t-1}) - \ln(c_{i,t-2})]$ under the assumption it is uncorrelated with $v_{it} - v_{i,t-1}$.

Table (5) presents Anderson-Hsiao instrumented first-difference estimates for each shock variable. Instrumenting the lagged dependent variable in first-difference estimation corrects for the Nickell bias. Most hurricane shock coefficients are insignificant, although negative. Permanent displacement and time of displacement are the only (weakly) significant effects: permanent displacement reduces consumption growth by nearly 26% within the treated sample. As concern other shock variables, floods take a negative coefficient (diminishing consumption growth by 7-9%) but remain marginally insignificant. Since the highest occurrence of floods is recorded in 1999 (table (3)), the flood coefficient is most probably attributable to Mitch. The result also suggests that local geographical idiosyncrasies beyond rainfall need to be considered to capture the impact of the hurricane. Overall, a conservative interpretation of these results reveal a limited direct welfare effect of hurricane Mitch at most through displacement and floods, not self-reported losses or exogenous rainfall[16].

3.4 Sensitivity analysis

Sensitivity of results to potential misspecifications such as violations of assumptions behind the Anderson-Hsiao estimator, weakness of the instruments, small sample or attrition bias are now successively discussed. The empirical methodology consistently estimates the negative idiosyncratic impact of the shock if it does not last until 2001. Persistence of the idiosyncratic component of the shock can be tested by introducing lagged shocks in the 1998-2001 or 1999-2001 growth equations. When this is done, none of the shock measures has a significant negative coefficient, ruling out persistent negative effects of the shock in the treated sample. Section 4 will show there are no persistent common effects of the shock in 2001 either.

The validity of the Anderson-Hsiao estimator relies on specific time-series properties of the error terms. Residuals are assumed to be serially uncorrelated, so that residuals in the first-difference equation have to be no more than AR(1) (Arellano & Bond, 1991)[17]. Tests for second-order serial correlation in first-difference residuals or alternative Sargan tests cannot be implemented in the exactly identified three time-series case. The fact that the Anderson-Hsiao

[16] Estimates for other controls are not displayed but diminutions of household's size (particularly female adults and male children) have positive effects on consumption growth throughout.

[17] In the context of growth models, measurement error can also lead to serial correlation in residuals (Bond et al., 2001).

estimates lie between first-difference and OLS estimates provides an informal confirmation of the validity of the model (Bond, 2002).

Anderson-Hsiao estimates can suffer from weak instruments which inflate standard errors and create a bias in direction of OLS estimates, even in large samples (Bound et al., 1995). In the context of dynamic panel data GMM estimators, high persistence in the endogenous variable can generate weak instruments problems (Bond, 2002). Here, the estimated model yields $\hat{\beta}$ close to -1. This reflects lack of persistence in the consumption series re-expressed in level, the opposite of the weak instrument random walk case. The strength of the instruments is confirmed by first-stage diagnostics in table (5).

Another potential issue is that semi-asymptotic consistency of Anderson-Hsiao estimators requires a large number of cross-sections. In small samples, the 2SLS estimator is biased toward the OLS estimator of the first-differenced equation (Bond, 2002). Since the size of the available sample is limited, Anderson-Hsiao estimates can therefore suffer from a residual small-sample downward bias. While such a bias could explain the magnitude of the lag consumption coefficient, it would only lead to overestimation of the identified negative impact of the hurricane.

Importantly, the nature of the results is robust to alternative specifications, for instance suppression of the dynamic structure or use of lag assets as controls for initial conditions instead of lag consumption. Displacement and flood coefficients remain at the border of significance levels, while all other measures of the shock are insignificant.

Attrition constitutes a potential worrying exception: attrition is 21.3% between 1998 and 1999 for agricultural households in the Mitch communities (25.9% between 1998 and 2001), but only 6.8% in non-Mitch communities between 1998 and 2001. If attrition is associated with the magnitude of the shock, estimates could suffer from an ommitted variable bias. The rainfall measure can be used to test for shock-induced attrition between 1998 and 1999. October 1998 rainfall average 421.5mm (an average excess of 238.8mm) among attritors and 553.2mm (an average excess of 370.4mm) for households surveyed in 1999. Differences are always significant at the 1% level between the two groups. Therefore, attrition is not correlated with higher rainfall. To the extent that rainfall is positively correlated with other shock measures for attritors (as it is for households in the sample), the high attrition rate should not create an upward bias in the above estimates.

In general, sensitivity analysis therefore suggests that Anderson-Hsiao estimates are conservative, most likely suffering from a downward bias which would reinforce the identified negative impact of hurricane losses. In the end, analysis of variations in short-term idiosyncratic hurricane-induced losses thus conclude to a very limited welfare impact, at most through households' displacement and floods[18].

[18] Results on the lack of effect of the hurricane are consistent with findings that the Nicaraguan overall poverty profile did not change between 1998 and 1999 (World Bank, 2001). It is also consistent with informal reports from microfinance institutions (e.g. FDL, Managua) stressing a remarkably low default rate on loans in the year after the hurricane.

4 Mitch's medium-term common impact

The analysis has so far focused on a treated sample by evaluating the impact of hurricane Mitch on consumption growth of affected agricultural households. This section now considers hurricane Mitch as a natural experiment. In 1999, INEC re-visited households surveyed in 1998 and located in communities hit by the hurricane (INEC, 2000). The medium-term impact of Mitch between 1998 and 2001 can be evaluated using INEC re-surveying decisions to characterise treatment (Baez and Santos, 2007)[19]. Re-surveyed households form the treatment group, while non re-surveyed households compose a control group. The approach contrasts with previous analysis of the short-term impact of relative losses within the sample of affected households. While the three–round panel deals with the idiosyncratic element of the shock, the 1998-2001 experimental set-up can identify persistence of its common dimension. The two alternative ways to exploit the data raise complementary questions. A medium-term impact between treatment and control groups does not imply a short-term impact of larger losses within the treatment group. Finding no medium-term impact between treatment and control groups does not rule out short-term effects either.

4.1 Treatment group

The composition of the treatment group warrants careful consideration. The criteria used by INEC (2000) to determine which "affected" communities were re-visited are not entirely transparent[20]. An important feature of the data is that at times INEC revisited some communities but not others in a same municipality. The extent to which a hurricane generates heterogeneous damage at the local level seems unclear a priori. This section considers whether a higher level definition of treatment is required because of propagation of the direct negative impact of the shock from re-surveyed to non-resurveyed communities[21].

The sample can be divided in three groups: households re-surveyed in 1999 (treated households), households located in non-resurveyed municipalities (control households outside municipality), and households located in non-resurveyed communities but in partly re-surveyed municipalities ("borderline group"). Table (6) contains descriptive statistics for welfare measures in these subgroups before and after Mitch. Descriptive statistics characterise outcomes but can

[19] Baez & Santos (2007) study Mitch's impact on children well-being. This section focuses on different outcomes and pushes further their experimental set-up by unveiling additional spatial patterns. These new patterns are unlikely to modify the interpretation of Baez & Santos' (2007) results as lower-bound estimates.

[20] "Households were selected for inclusion in the post-Mitch survey strictly on the basis that they were located in areas that were : (a) affected by the hurricane; and (b) included in the original 1998 LSMS" (World Bank, 2001).

[21] Households moving between 1998 and 2001 constitute another concern as regards the appropriateness of the treatment group. Only 20 households have different community location in 1998 and 2001. Since communities are non-official in Nicaragua, these changes might reflect fuzzy borders rather than proper movements. Classification is left unchanged but has no implications on results. The panel does not contain households who changed municipalities between 1998 and 2001.

be used to scrutinise INEC re-surveying procedure. *A priori*, adverse post-hurricane effects for the borderline group could provide evidence against local heterogeneity of the hurricane's direct impact. Propagation of the shock would suggest that the treatment group based on INEC definition is too narrow. Table (6) highlights important contrasts. Initial consumption is largest in the outside control group and smallest in the treatment group. 2001 consumption is highest in the borderline group and still smallest in the treatment group. Although the initial difference between treatment and borderline group is not significant, the borderline group diverges and has significantly higher consumption in 2001[22]. Descriptive statistics thus show no evidence of propagation of the negative impact of the shock at the local level.

The relevance of broader measures of the shock can nevertheless be considered. TRMM October 1998 rainfall provide a municipal measure of Mitch's impact and can be modelled in 1998-2001 growth equations[23]:

$$\ln(c_{i,t}) - \ln(c_{i,t-1}) = \alpha + \gamma MITCH_{i,t} + \delta X_{i,t} + \varepsilon_{i,t} \quad (3)$$

In table (7), municipal-level rainfall measures are positive, although not always significant. Similar results appear when a municipal Mitch dummy is used. No evidence of negative common impact of the shock measured at the municipal level appears either.

There is thus no evidence to reject INEC community-level treatment definition[24] in favour of a higher-level definition. However, crucial identification challenges arise from the substantial spatial heterogeneity unveiled in table (6): next section further shows that the identified municipal-level effects are driven by non-affected households in affected municipalities (borderline group).

4.2 Difference-in-differences estimates

This section presents difference-in-differences estimates between the treatment group and various control groups. The first "all controls" group (812 households) is taken as the complement of the treatment group (204 households). The second control group is formed of 136 households of the borderline group (within-municipality controls) and will allow tackling municipal-level unobservables. The third alternative control group contains 676 households in non-resurveyed municipalities (outside municipality controls). Table (8) contains

[22] The difference in consumption between treatment and borderline groups is marginally insignificant in 1998 (p=0.15), but significant in 2001 (p=0.05). The related growth rate is marginally insignificant (p=0.14). Since consumption is equal in 1998 but not in 2001 within municipalities, and as no negative impact of the hurricane appears for the borderline group, the heterogenous impact of hurricane Mitch at the local level cannot be rejected. The significance of differences in consumption between other groups is discussed in section 4.2

[23] X contains the same set of controls as in section 3. Three specifications are considered: no controls (I), X as controls (II), X and lag consumption as controls (III). Specification (III) makes results comparable with those from section 3.

[24] Within-municipality heterogeneity of the direct impact of the hurricane implies that the rainfall measure is not generally accurate enough. However, it remains relevant when focusing on the treated sample as in section 3.

descriptive welfare statistics for treatment and control groups. 1998 consumption is lower for the treatment group and significantly so, apart from within-municipality controls. By contrast, equality of 2001 consumption can only be rejected when within-municipality controls are considered. While the initial consumption differential within municipalities has narrowed, the corresponding differences in growth rates are never significant. The treatment group displays significantly higher growth compared to control households outside of the municipality, however. This suggests that outside municipality controls might not provide the adequate counterfactual and prevent identification of the hurricane's impact when all control households are pooled.

Difference-in-differences estimates can be obtained by OLS as follows:

$$\ln(c_{i,t}) - \ln(c_{i,t-1}) = \alpha + \gamma MITCH_{i,t} + \delta \Delta X_{i,t} + \varepsilon_{i,t} \tag{4}$$

Treatment effects (γ) are estimated for three control groups[25] and presented in table (9). Estimates relate to growth equations for the three-round panel. Control variables are included to account for pre-shock observed differences between treated and control households (table (10)). No significant medium-term common effect of the hurricane is identified. Coefficients are positive for all control households and control households outside municipalities. Negative effects appear when within-municipalities control households are considered. While they remain insignificant, they again suggest existence of spatial heterogeneity.

Two sets of earlier results already pointed to such heterogeneity. First, municipal shock measures are associated with larger consumption growth, which is driven by control households in affected municipalities. Second, albeit insignificant, a growth shortfall is identified for the treatment group compared to within-municipality control households. Importantly, these results cannot be attributed to the hurricane if initial growth potentials differ in treatment or control groups. Jalan & Ravallion (1998) show how spatial dependence in the growth process leads to underestimation of development program benefits when growth paths of areas not covered by the program do not provide an adequate counterfactual. By the same token, higher initial growth potential for affected households could explain both vanishing hurricane losses and some of the positive effects uncovered in tables (7) or (8).

Differences in underlying growth paths for treated households could be driven by heterogeneity at both the household and municipal levels. Table (10) displays differences in pre-shock control variables between treatment and control households. While initial consumption is not different between treatment and within-municipality control households, patterns regarding other variables are less clear and reveal slightly more within-municipality than betwen-municipality differences. Such observed household-level differences are accounted for in difference-in-differences estimation. On the other hand, table (11) displays municipal averages for demographics, private and public assets from the 1995 Nicaraguan

[25] Estimates as presented without controls (I) and with X as controls (II). The set of control variables in the same as in section 3, with all variables taken as differences between the two rounds to yield difference-in-differences estimates.

census. Even when there is little significant differences between treatment and control households in the survey, table (11) suggests unobserved heterogeneity might remain at the municipal level. Treatment municipalities are generally less well-endowed in private assets and there is weaker evidence of differences in local public assets (access to health care). Such observed heterogeneity can support the presence of spatial externalities in the growth process (Jalan & Ravallion, 1998). In absence of within-municipality location data, common municipal trends can be introduced in difference-in-differences estimation based on the within-municipality control groups. Table (9) shows that both between-municipality and household-level differences account for part of the previous non-significant negative within-municipality effects. In the end, controlling for unobserved municipal heterogeneity and observed within-municipality pre-shock differences confirm the absence of significant common negative impact of hurricane Mitch in the medium-term.

4.3 Sensitivity analysis

Difference-in-differences estimation relies on crucial assumptions. First, INEC (2000) community-level classification needs to accurately characterise the extent of the hurricane's immediate impact. As explained, outcomes from available data do not suggest otherwise. Second, identification relies on absence of other sources of within-municipality heterogeneity apart from Mitch's direct impact and observed household-level pre-shock differences.

INEC re-surveyed communities based on assessment of direct damage, but the hurricane can also generate differentiated indirect effects within municipalities. Difference-in-differences estimators rely on a "same time-effect assumption" requiring the untreated response to change "by the same magnitude on average for both regions" (Lee, 2005, p.101). Between 1998 and 2001, affected regions might have benefited from post-hurricane responses (e.g. aid) or suffered negative indirect effects (e.g. local economic downturn). Implications of within-municipality heterogeneity can be analysed in terms of omitted variable bias through the error term of equation (4). Crucially, estimates only identify the net effect of hurricane Mitch between treatment and control groups. In this sense, post-shock indirect effects of equal intensity for both groups are captured by the constant term and municipality trends, along with other common unobservables. However, if indirect effects are stronger for the treatment or control groups, only the combination of the hurricane direct and indirect impacts can be identified.

The implications of particular forms of within-municipality heterogeneity related to positive post-disaster responses, indirect impact of the shock and underlying community dynamics can be sketched as follows. First, if municipalities affected by hurricane Mitch received well-targeted public aid, treatment households should have benefited relatively more than control households. This would not justify revising the conclusion that the shock has no impact in the medium-term, but would rather provide an explanation of the mechanisms mitigating Mitch's direct impact. Such mitigation mechanisms should tend to limit

the observed difference in growth rates between control and treatment groups, but do not create inconsistencies in the estimation procedure. Second, propagation of the indirect negative impact (e.g. economic downturn) of the shock could possibly constitute a more serious issue. If the control group suffers disproportionately, the net consumption shortfall for the treatment group could be underestimated. Still, it appears more probable than the treatment group also suffers comparatively more from indirect shock spillovers in comparison to the control group. In this case, the identified non-significant negative effects is overestimated, not weakened. Finally, heterogeneity in the direct impact of the shock might not be purely random. Local geographical idiosyncrasies can be correlated with unobserved differences in underlying dynamics between communities within the same municipality. Higher underlying growth in treatment communities could weaken the identified and non-significant negative impact of Mitch. Beyond controlling for observed household-level characteristics, such within-municipality unobserved heterogeneity cannot be ruled out. However, rural communities in Nicaraguan municipalities often share major climatic factors and local dynamics remain very homogeneous, so it remains unlikely that survey-based variables are insufficient to account for local differences.

Previous results concluded to a non-significant impact of hurricane Mitch on consumption growth of treated households, even accounting for spatial heterogeneity. This section has stressed that the methodology identifies the impact of the shock net of indirect effects and mitigation mechanisms. It appears unlikely that unobserved within-municipality heterogeneity explains the absence of significant negative impact of hurricane Mitch on medium-term consumption growth, but no formal testing can be performed beyond control for observed differences. With this word of caution, the analysis concludes that Mitch did not have a significant persistent common negative impact on consumption of Nicaraguan agricultural households after three years. Tracing back to section 3, the experimental analysis backs the validity of the 1999 sample on which the three-round panel is built. Section 4 also confirms that 1998-1999-2001 consumption growth equations do not fail to identify the effect of the shock because of its persistence. Finally, the experimental analysis echoes results from section 4 on the limited persistence of hurricane Mitch's direct welfare impact.

5 Conclusion

This paper contributes to the literature linking risk and welfare dynamics. The unique design of Nicaraguan data is exploited in order to assess the persistence of hurricane Mitch's direct welfare effects. The analysis unpacks the hurricane's short and medium term impacts, disentangles its idiosyncratic from its common dimension and highlights the main channels through which it affects agricultural households' consumption growth. Descriptive statistics show no evidence of a large consumption downfall post-Mitch. Households' welfare experiences are particularly diverse in the Mitch panel. Self-reported hurricane-induced losses are on average larger than annual consumption of two household mem-

bers, but magnitude and incidence patterns exhibit significant heterogeneity. TRMM data are interpolated at the municipal level to provide a complementary measure of the shock. The analysis first considers whether relative variations in hurricane damage explain heterogeneity of short-term consumption growth. An empirical growth model is estimated for the panel of treated agricultural households. Estimates reveal the hurricane's very limited welfare impact in the short-term, at most through floods and households' displacement, but not self-reported losses or rainfall. Relative magnitude of hurricane losses offer little explanation for variations of short-term consumption growth of affected Nicaraguan agricultural households.

The complementary natural experiment set-up focuses on Mitch's common medium-term impact between 1998 and 2001. Definition of treatment status is based on INEC re-survey of communities considered damaged by Mitch. Not all communities are classified uniformly within municipalities: the shock has a heterogeneous direct impact at the local level. Overall, while Mitch does not aggravate the consumption gap between affected and non-affected households, substantial diversity appears. Differences in underlying growth potential for treated and control households could explain vanishing hurricane losses. Municipal shock measures show evidence of higher growth in regions hit by the hurricane, driven by households in control communities. Such spatial heterogeneity stems from differences at both the household and municipality levels, but remains insufficient to explain the hurricane's absence of negative effect. In the end, the two components of the analysis consistently point to, at most, a very limited short-term idiosyncratic effect of the hurricane on consumption growth of Nicaraguan agricultural households. In sharp contrast with the large magnitude of reported losses at both the macro (ECLAC, 2000) and micro levels (Morris et al., 2002; section 2 above), Mitch's direct welfare impact thus exhibits little persistence.

Such conclusions do not invalidate the link between shocks and welfare dynamics. Indeed, estimation procedures identify Mitch's impact net of risk-coping mechanisms and as such results suggest mitigation was effective in preventing direct welfare effects. Recent explanations in the context of hurricane Mitch involve social networks (Carter and Castillo, 2005), asset liquidation (Carter et al. 2007) and diminution of investment in children's human capital (Baez and Santos, 2007). Other suggestive rationales can also be offered. First, widespread baseline drought can explain part of Mitch's limited impact. Second, Mitch struck Nicaragua just before the six-month dry season. Extraordinary rainfall induced by the hurricane might have prolonged the fertility of soils and allowed a third harvest in regions where drought usually makes it impossible (MAGFOR, 1999). Additional explanations involve aid, women's increased labour-market participation (INEC, 2000) and migration. While effective mitigation is surprising in the context of a large common shock, it contrasts with evidence on less spectacular events (Dercon, 2005). Finally, non-persistence of the direct welfare impact of the shock and effective mitigation in the short-term do not rule out all adverse welfare effects since risk-coping can be costly over a longer time horizon. In this sense, the paper complements rather than contra-

dicts recent evidence on children's' well-being (Baez & Santos, 2007) or asset liquidation (Carter et al. 2007). In absence of persistent direct effects, Mitch's welfare impact is likely to reveal itself through indirect channels over the longer term.

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6 Appendix

6.1 Satellite rainfall data[26]

NASA Tropical Rainfall Measurement Mission's (TRMM) interface provides worldwide satellite monthly accumulated rainfall observations on a grid of 0.25 degrees of longitude by 0.25 degrees of latitude (approximately 28 km^2 in Nicaragua) starting in 1998. TRMM rainfall collection combines both a precipitation radar and a microwave radiometer (Adler et al. 2000).

Figure (1) reproduces rainfall for October 1998 for a window covering the Nicaraguan territory (-88 to -82.5 degrees of longitude West; 10.5 to 15.5 degrees of latitude North). The window contains 483 data points, and each depicted square 9 observations.

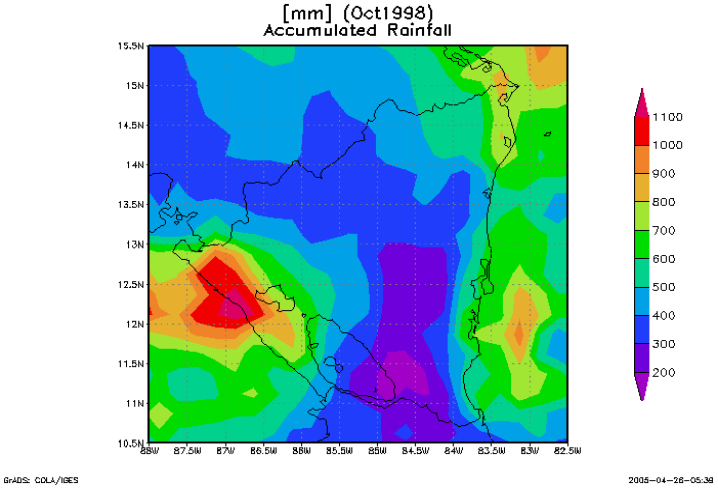

Figure 1: Accumulated Rainfall (mm) in Nicaragua, October 1998 (Source: NASA TRMM)

Municipal coordinates do not correspond to grid nodes and interpolation is required to infer municipal rainfall. Bilinear interpolation generalises linear interpolation to three-variable cases. Consider figure (2) where x denotes the longitude axis and y the latitude axis. Interpolation of rainfall value f is performed at point $M = (x^*, y^*)$. Rainfall observations are available from

[26] The rainfall data used in this paper were acquired as part of the Tropical Rainfall Measuring Mission (TRMM). The algorithms were developed by the TRMM Science Team. The data were processed by the TRMM Science Data and Information System (TSDIS) and the TRMM Office; they are archived and distributed by the Goddard Distributed Active Archive Center. TRMM is an international project jointly sponsored by the Japan National Space Development Agency (NASDA) and the U.S. National Aeronautics and Space Administration (NASA) Office of Earth Sciences. Bilinear interpolation of TRMM data at Nicaraguan municipal centres was programmed by the author using STATA.

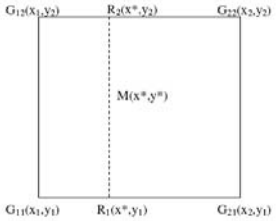

Figure 2: Bilinear interpolation at M from four grid points

TRMM at the four grid nodes $G_{11} = (x_1, y_1)$, $G_{12} = (x_1, y_2)$, $G_{21} = (x_2, y_1)$ and $G_{22}(x_2, y_2)$.

Linear interpolation is first performed in one direction (longitude here):

$$f(R_1) \approx \frac{x^* - x_2}{x_1 - x_2} f(G_{11}) + \frac{x^* - x_1}{x_2 - x_1} f(G_{21})$$

$$f(R_2) \approx \frac{x^* - x_2}{x_1 - x_2} f(G_{12}) + \frac{x^* - x_1}{x_2 - x_1} f(G_{22})$$

Interpolation is then performed in other direction (latitude here), yielding the desired estimate of f(M).

$$f(M) \approx \frac{y^* - y_2}{y_1 - y_2} f(R_1) + \frac{y^* - y_1}{y_2 - y_1} f(R_2)$$

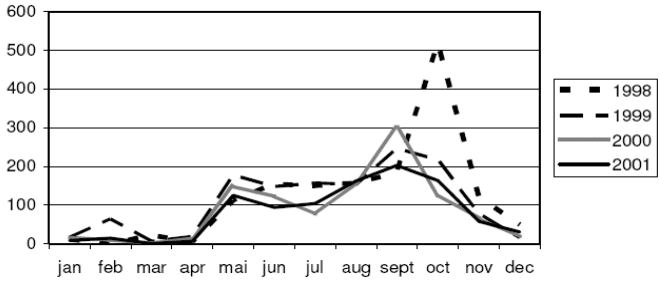

Figure 3: Average municipal monthly rainfall estimated by bilinear interpolation from NASA TRMM data (mm, 123 municipalities)

The method was programmed by the author using municipal coordinates from INEC. Figure (3) summarises interpolated average monthly rainfall for 123 Nicaraguan municipalities. Interpolated values from TRMM data were also compared to gauge data from available Nicaraguan stations and performed well.

6.2 Tables

	1998-2001 panel	Mitch panel	Mitch panel	Mitch panel	1998-2001 panel
	1998		1999	2001	
Poverty	68.7%	74.1%	73.1%	70.6%	63.6%
Extreme Poverty	28.6%	32.0%	34.5%	25.9%	25.4%
Consumption (C$)	4149.4	3599.7	3687.3	3516.6	3965.5
	(3982.7)	(2625.6)	(3124.3)	(2496.8)	(3971.0)
Consumption (ln,C$)	8.08	7.99	8.00	7.99	8.04
	(0.67)	(0.62)	(0.63)	(0.57)	(0.66)
Consumption growth	.	.	0.01	-0.01	-0.04
	.	.	(0.58)	(0.60)	(0.61)
Observations	1016	197	197	197	1016

note: 1998 prices (in cordobas); poverty line: 4223C$, extreme poverty line: 2489C$; average cordoba-dollar exchange rate in 1998: 10.58; standard deviations in parenthesis; growth from previous round; all values computed from Nicaraguan LSMS.

Table 1: Descriptive welfare statistics (1998-2001 and Mitch agricultural panels)

	Incidence		*Average per household*	
Self-reported losses	n	%	Mean	St.Dev.
Capital losses (ln, C$)	57	29%	1182.1	3636.0
Livestock losses (ln, C$)	127	64%	1977.6	6254.9
Total asset losses (ln, C$)	141	72%	3159.7	9053.4
Output losses (ln, C$)	186	94%	5211.2	8409.8
Total losses (ln, C$)	190	96%	8370.9	13287.1
Displacement and housing destruction	n	%	Mean	St.Dev.
Permanent displacement	19	10%	0.10	.
Temporary displacement	48	24%	0.24	.
Displacement	67	34%	0.34	0.47
Displacement days (ln, days)	67	34%	28.26	71.94
Housing damage index (0-8)	96	49%	3.69	4.96
Rainfall shock measures	n	%	Mean	St.Dev.
Rainfall October 1998 (mm)	197	100%	538.74	200.42
Rainfall Excess October 1998 (mm)	197	100%	352.67	188.25
Rainfall October 1998 (ln, mm)	197	100%	6.23	0.35
Rainfall Excess October 1998 (ln, mm)	197	100%	5.69	0.66
Flood	30	15%	0.15	.

note: shock measures for 197 agricultural households in 1998-1999-2001 panel; self-reported losses in cordobas; asset losses aggregate capital and livestock; housing destuction index ranges from 0 to 8; all measures from 1999 LSMS apart from rainfall; rainfall interpolated at municipal centre from NASA TRMM observations.

Table 2: Hurricane shock measures

	1999		*2001*	
	Mean	St.Dev.	Mean	St.Dev.
Drought (Δ)	-0.41	0.61	0.21	0.64
Pest (Δ)	-0.06	0.69	0.24	0.68
Floods (Δ)	0.11	0.43	-0.10	0.42
Other shocks (Δ)	-0.05	0.40	0.02	0.35
N male children (Δ)	0.04	0.85	-0.19	0.99
N male adults (Δ)	-0.04	0.74	0.10	0.87
N female children (Δ)	-0.04	0.62	-0.12	1.04
N female adults (Δ)	0.01	0.61	0.03	0.81
Female household head	0.09	0.29	0.13	0.33
Household head's age	48.17	15.04	49.23	15.11
Education per adult	2.50	1.99	2.63	1.91

note: control variables for 197 agricultural households in 1998-1999-2001 panel; shocks and demographics in difference between t and t-1, other variables at t-1.

Table 3: Descriptive statistics (control variables for growth equations)

	I	II	III	IV	V	VI	VII	VIII
	coef/sd	coef/sd	coef/sd	coef/sd	coef/sd	coef/sd	coef/sd	coef/sd
Initial consumption	-0.47***	-0.47***	-0.47***	-0.47***	-0.47***	-0.47***	-0.47***	-0.47***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Total hurricane losses (ln, C$)	0.01							
	(0.01)							
Total capital losses (ln, C$)		0.01						
		(0.01)						
Total output losses (ln, C$)		0.00						
		(0.01)						
October 1998 rainfall (ln, mm)			0.01					
			(0.01)					
October 1998 excess rainfall (ln, mm)				0.01				
				(0.01)				
Pemanent displacement					-0.04			
					(0.11)			
Displacement						0.02		
						(0.07)		
Displacement time (ln, days)							-0.01	
							(0.02)	
Housing damage index								0.00
								(0.01)
Flood (Δ)	-0.09	-0.09	-0.09	-0.09	-0.08	-0.09	-0.08	-0.09
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Number of observations	393	393	393	393	393	393	393	393
Adjusted R2	0.360	0.358	0.359	0.359	0.358	0.358	0.358	0.359
F	17.93	16.64	17.85	17.87	17.81	17.80	17.81	17.85

note: .01 - ***; .05 - **; .1 - *; Pooled OLS for household consumption growth in 1998-1999 and 1999-2001; robust standard errors; controls include initial education, household head's age and sex, as well as differences between rounds for drought, pest, other agricultural shocks, number of male adults, female adults, male children and female children.

Table 4: Pooled OLS estimates (consumption growth)

	I	II	III	IV	V	VI	VII	VIII
Second-stage	coef/sd	coef/sd	coef/sd	coef/sd	coef/sd	coef/sd	coef/sd	coef/sd
Initial consumption	-0.78***	-0.77***	-0.78***	-0.78***	-0.79***	-0.82***	-0.83***	-0.77***
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.17)
Total hurricane losses (ln, C$)	0.01							
	(0.02)							
Total capital losses (ln, C$)		-0.01						
		(0.01)						
Total output losses (ln, C$)		0.02						
		(0.02)						
October 1998 rainfall (ln, mm)			-0.13					
			(0.14)					
October 1998 excess rainfall (ln, mm)				-0.05				
				(0.07)				
Pemanent displacement					-0.26*			
					(0.15)			
Displacement						-0.14		
						(0.10)		
Displacement time (ln, days)							-0.05*	
							(0.02)	
Housing damage index								0.00
								(0.01)
Flood (Δ)	-0.09	-0.09	-0.09	-0.09	-0.07	-0.08	-0.07	-0.09
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Number of observations	196	196	196	196	196	196	196	196
Adjusted R2	0.635	0.633	0.638	0.636	0.642	0.655	0.659	0.632
F	9.84	9.04	9.71	9.67	10.04	10.27	10.60	9.58
First-stage: Instrument coefficient and diagnostics								
Initial consumption (lag)	-0.46***	-0.46***	-0.45***	-0.45***	-0.45***	-0.45***	-0.45***	-0.45***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Number of observations	196	196	196	196	196	196	196	196
Adjusted R2	0.295	0.289	0.297	0.288	0.275	0.276	0.275	0.277
F	7.27	6.67	7.35	7.06	6.69	6.72	6.69	6.76

note: .01 - ***; .05 - **; .1 - *; Anderson-Hsiao 2SLS estimates for difference in consumption growth between 1999-2001 and 1998-1999; 1998 consumption serves as instrument for difference in initial conditions (along with other controls); controls include initial education, household head's age and sex, as well as differences between rounds for drought, pest, other agricultural shocks, number of male adults, female adults, male children and female children.

Table 5: Anderson-Hsiao 2SLS estimates (consumption growth)

		1998		*2001*		*Growth 1998-2001*	
	N	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Treatment group	204	8.00	0.62	7.99	0.57	0.00	0.60
Borderline group	136	8.04	0.63	8.11	0.64	0.06	0.57
Outside municipality controls	676	8.11	0.69	8.04	0.69	-0.07	0.62

note: descriptive statistics for 1998-2001 agricultural panel; treated households are those re-surveyed in 1999; borderline group contains non-resurveyed households located in municipalities with some re-surveyed households; outside municipality controls are located in municipalities without re-surveyed households.

Table 6: Descriptive statistics (consumption across space in 1998-2001 panel)

	I	II	III	I	II	III
	coef/sd	coef/sd	coef/sd	coef/sd	coef/sd	coef/sd
Rainfall October 1998 (ln, mm)	0.10	0.06	0.10			
	(0.06)	(0.06)	(0.06)			
Muncipal Mitch dummy				0.10*	0.07	0.03
				(0.05)	(0.05)	(0.05)
Controls		yes	yes		yes	yes
Initial consumption			yes			yes
Number of observations	1,016	1,013	1,013	1,016	1,013	1,013
Adjusted R2	0.002	0.130	0.314	0.005	0.132	0.311

note: .01 - ***; .05 - **; .1 - *; OLS; clustered standard errors; controls include initial education, household head's age and sex, as well as differences between rounds for drought, pest, other agricultural shocks, number of male adults, female adults, male children and female children.

Table 7: OLS for 1998-2001 consumption growth and municipal shock measures

		1998		2001		1998-2001 growth	
	N	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Treatment group	204	8.00	0.62	7.99	0.57	-0.00	0.60
All controls	812	8.10	0.68	8.05	0.68	-0.05	0.62
Difference	.	-0.104**	0.05	-0.06	0.05	0.05	0.05
Treatment group	204	8.00	0.62	7.99	0.57	-0.00	0.60
Within municipality controls	136	8.04	0.63	8.11	0.64	0.06	0.57
Difference	.	-0.045	0.07	-0.114**	0.07	-0.069	0.07
Treatment group	204	8.00	0.62	7.99	0.57	-0.00	0.60
Outside municipality controls	676	8.11	0.69	8.04	0.69	-0.07	0.62
Difference	.	-0.115**	0.05	-0.045	0.05	0.070*	0.05

note: descriptive statistics for 1998-2001 agricultural panel; treated households are those re-surveyed in 1999; within-municipality controls are located in municipalities with some treated households; outside municipality controls are located in municipalities without treated households.

Table 8: Consumption in treatment and control groups

	I	II	I	II	I	II	I	II
	coef/sd	coef/sd	coef/sd	coef/sd	coef/sd	coef/sd	coef/sd	coef/sd
All controls	0.05	0.05						
	(0.07)	(0.06)						
Within municipality controls			-0.07	-0.02			-0.05	0.03
			(0.07)	(0.06)			(0.08)	(0.07)
Outside municipality controls					0.07	0.06		
					(0.07)	(0.07)		
Controls		yes		yes		yes		yes
Municipal trend							yes	yes
Number of observations	1,016	1,013	340	338	880	878	340	338
Adjusted R2	0.000	0.128	0.000	0.094	0.001	0.127	0.16	0.25

note: .01 - ***; .05 - **; .1 - *; OLS for 1998-2001 agricultural panel; clustered standard errors; treated households are those re-surveyed in 1999; within-municipality controls are located in municipalities with some treated households; outside municipality controls are located in municipalities without treated households; control variables include initial education, household head's age and sex, as well as differences between rounds for drought, pest, other agricultural shocks, number of male adults, female adults, male children and female children.

Table 9: Difference-in-differences estimates

	All controls			*Within municipality controls*			*Outside municipality controls*		
	Control	Treatment	p	Control	Treatment	p	Control	Treatment	p
Consumption (ln, C$)	8.10	8.00	0.02	8.04	8.00	0.26	8.11	8.00	0.20
Drought	0.89	0.85	0.10	0.93	0.85	0.01	0.88	0.85	0.56
Pest	0.57	0.55	0.27	0.72	0.55	0.00	0.54	0.55	0.04
Floods	0.07	0.04	0.07	0.03	0.04	0.76	0.08	0.04	0.11
Other shocks	0.13	0.11	0.18	0.09	0.11	0.72	0.14	0.11	0.54
N male children	1.51	1.51	0.53	1.52	1.51	0.48	1.50	1.51	0.76
N male adults	1.91	1.95	0.64	2.06	1.95	0.19	1.88	1.95	0.69
N female children	1.48	1.49	0.54	1.69	1.49	0.11	1.44	1.49	0.93
N female adults	1.67	1.71	0.70	2.03	1.71	0.01	1.60	1.71	0.46
Female hh head	0.10	0.10	0.39	0.13	0.10	0.22	0.10	0.10	0.89
Household head's age	46.47	47.54	0.81	48.85	47.54	0.22	45.99	47.54	0.24
Education per adult	2.76	2.51	0.09	3.36	2.51	0.00	2.64	2.51	0.15
Assets (ln, C$)	7.80	7.68	0.26	7.79	7.68	0.31	7.80	7.68	0.26
Livestock (ln, C$)	6.69	6.57	0.32	6.52	6.57	0.56	6.72	6.57	0.28
Durable goods (ln, C$)	5.33	5.25	0.31	5.48	5.25	0.15	5.30	5.25	0.38
Number of observations	812	204		204	136		204	676	

note: Averages for treatment and control group from 1998-2001 agricultural panel; treated households are those re-surveyed in 1999; within-municipality controls are located in municipalities with some treated households; outside municipality controls are located in municipalities without treated households; p-value for test of difference in means between treatment and control groups.

Table 10: Mean of pre-shock variables in treatment and control groups

	Control	Treatment	p
Demograghics and education			
N Male household member	3.11	3.12	0.62
N Female household member	3.08	3.10	0.97
Female household head	0.21	0.22	1.00
Catholic	0.59	0.60	0.83
Literate	0.47	0.49	0.99
School enrollment	0.63	0.68	1.00
Primary school completion	0.26	0.27	0.90
Secondary school completion	0.08	0.08	0.77
Dwelling characteristics (private assets)			
Ownership title	0.48	0.43	0.00
Brick wall	0.43	0.49	0.99
Wooden wall	0.51	0.44	0.00
Zinc roof	0.51	0.42	0.00
Tile roof	0.29	0.38	1.00
Dirt floor	0.65	0.64	0.23
Tile floor	0.13	0.10	0.00
Brick floor	0.24	0.21	0.01
Number of rooms	2.17	2.07	0.00
Number of bedrooms	1.56	1.54	0.02
Latrines	0.57	0.55	0.14
Toilets	0.06	0.07	0.97
Use of animal to go to health centre	0.09	0.07	0.00
Use of vehicle to go to health centre	0.08	0.08	0.71
Public assets (infrastructure)			
Access to water	0.16	0.15	0.21
Get water from river	0.27	0.26	0.30
Get water from well	0.28	0.31	0.99
Connection to sewing system	0.03	0.05	0.99
Electricity	0.37	0.35	0.15
Kids born with birth certificate	0.67	0.67	0.33
Average time to health centre	0.98	0.85	0.00
Dispersion (st.dev.(time to health centre))	1.19	1.02	0.00

note: Average of municipal-level characteristics between households in treatment and control groups; municipal averages are from 1995 Nicaraguan census, p-value for test of difference in means between treatment and control groups.

Table 11: Municipal characteristics from 1995 Nicaraguan census