UNIVERSITY OF FLORENCE

Department of Economics and Management

Federico Ciani and Donato Romano

Testing for Household Resilience to Food Insecurity: Evidence from Nicaragua

Abstract

The main goal of this paper is to develop a methodology to quantitatively assess resilience to food insecurity. The developed methodology is applied to Nicaraguan rural households hit by Mitch Hurricane in 1999. The results show that the proposed resilience index is a good predictor of households' food security. The proposed resilience index highlights small landowners and agricultural wage workers as less resilient vis-à-vis other livelihood groups. Moreover this paper shows how a resilience index can be used in policy impact evaluation.

JEL classification: Q12, Q18, I32, I38

Keywords: Resilience, Agriculture, Food Security, Nicaragua

1. Introduction

The overall objective of this paper is to develop a suitable method to measure household resilience to shocks in the domain of food security and to test it using a panel dataset allowing a dynamic specification. As a result, there are three main empirical research questions we address, namely: (i) how can household resilience to food insecurity be measured? (ii) does household resilience contribute to ensuring household food security? and (iii) if so, what are the policy implications of it?

Referring to Barrett and Constas (2012: 4) remarks about alternative views of the expected function of the resilience concept – a more "normative" one (i.e. building causal models linking risks, ex ante protections and ex post responses) vs. a more "positive" one (i.e. understanding and describing how a set of resilience-enhancing capacities can improve well-being) – our analysis belong to the former approach. Moreover, rather than giving a "procedural" account of how to measure resilience, we will use here a "substantive" notion of measurement, that is we propose an approach for measuring household resilience, the so-called resilience index, to be used as a predictor of future well-being outcomes, i.e. food security. The tradeoff implicit in this modeling effort is, as usual, between a statistically more robust estimate of the relationships among variables and the implied loss in terms of ability capture the richness of the myriad specific situations in terms of how people are endowed by an asset portfolio, the stressors and shocks they may experience and the way they try to prevent, manage and cope with those disturbances. Though acknowledging the implicit risk in this ultra-reductionist exercise, we decided to bear it because our focus is on whether and how household resilience, as measured by our resilience index, impact future well-being outcomes.

The paper is structured as follows. Next section briefly reviews the empirical approaches to resilience measurement and describes the original contributions of this paper. The third section introduces the case study – the impact of Mitch hurricane on rural households Nicaragua – and presents the results of the analysis, namely (i) the resilience index, (ii) the validation of the index and (iii) the possible use of the index in an impact evaluation framework. The last section summarizes the main findings of the paper.

2. Approaches for a Quantitative Assessment of Household Resilience to Food Insecurity

2.1. Resilience to Food Insecurity

Following Dercon (2001: 16-19) we maintain that "households and individuals have assets, such as labour, human capital, physical capital, social capital, commons and public goods at their disposal to make a living. Assets are used to generate income in various forms, including earnings and returns to assets, sale of assets, transfers and remittances. Households actively build up assets, not just physical capital but also social or human capital, as an alternative to spending. Incomes provide access to dimensions of well-being: consumption, nutrition, health, etc., mediated by information, markets, public services and non-market institutions. Generating incomes from assets is also constrained by information, the functioning of markets and access to them, the functioning of non-market institutions, public service provision and public policy. … Risks are faced at various steps in this framework." Assets, their transformation into incomes and in turn their transformation into dimensions of well-being are all subject to risk.

According to this framework, well-being and any dimension of it like being food secure or poverty, are ex-post measure of the household decision-making process about their assets and incomes while faced with a variety of risks. Vulnerability to food insecurity describes the outcome of this process *ex-ante*, i.e. considering the potential outcomes rather then the actual outcome. Food insecurity is measured at a point in time, 'a snapshot', but vulnerability is essentially forward-looking, using the information at a particular point in time. Vulnerability would be the propensity to fall below the (consumption) threshold and its assessment thereby deals not only with those who are *currently* poor but also those who are *likely to be* poor in the future (Chaudhuri *et al*., 2002). Vulnerability to food insecurity is then determined by:

a) the risks faced by households and individuals when making a living;
b) the options available to households (individuals, communities) to make a living (including assets, activities, market and non-market institutions, public services provision);
c) the ability to handle this risk.

We argue that vulnerability is function of household's risk exposure and of household resilience to such risks and we adopt an output-based framework of analysis, i.e. in the same vein of the 'asset-income-outcome' causal chain suggested by Dercon (2001). Therefore household resilience to food insecurity can be defined as the ability of a household to keep with a certain level of well-being (i.e. being food secure) by withstanding shocks and stresses, and reorganize while undergoing change so as to still retain essentially the same function, structure, and identity.[1] It depends on the options available to the household to make a living and on its ability to handle risks. It refers therefore to ex-ante actions aiming at reducing or mitigating risks as well as ex-post actions to cope with those risks; and it covers both short-term actions (e.g. coping) and actions that have an impact on the longer-term (e.g. adaptation to structural changes

[1] This concept of resilience is essentially the same as 'development resilience' as defined by Barrett and Constas (2012).

so that the household 'functionings' will be ensured). The focus of our empirical application is on how to measure resilience to food insecurity as a contribution to vulnerability assessment.

2.2. Empirical Approaches to Quantitative Assessment

There are very few studies that have tried to quantitatively assess household's resilience to food insecurity (Annex 1). The main problem with a quantitative approach to resilience measurement is that resilience is not directly observable. There are two possible strategies to overcome this problem: modeling resilience as a latent variable (Alinovi *et al*., 2008 and 2010; Mulat and Negussie, 2010) or using an observable variable as a proxy of resilience (Carter *et al*., 2006; Keil *et al*., 2008).

Alinovi *et al*. (2008 and 2010) model resilience as a multidimensional latent variable, which is estimated using cross-sectional household data from the Kenya integrated household budget survey and from the Palestinian public perception survey respectively. The household resilience is supposed to be determined by various components: (i) social safety nets, (ii) access to public services, (iii) assets, (iv) income and food access, (v) stability and (vi) adaptive capacity. These components are, in turn, not directly measurable and are considered as latent variables themselves. Therefore, the authors design a two-stage process to resilience assessment. In the first stage the observed variables are used to estimate a first set of latent variables through a factor analysis. These latent variables are, in turn, used to compute a resilience index through the same technique. In Alinovi *et al*. (2010) the analysis is enriched by the use of cluster analysis to classify the population in six sub-groups corresponding to six livelihood strategies. In doing so it is possible to highlight how different livelihood groups (i.e. strategies) are related to different resilience levels and resilience building mechanisms.[2]

Mulat and Negussie (2010) tried to estimate household's resilience to food insecurity in a dynamic context by using micro-panel data from the Ethiopian rural households survey. Resilience is considered as a latent variable and it is estimated through a Principal Component Analysis (PCA) run on four variables: food access, liquid assets, education, social network. Then the authors estimate a panel fixed effect model and a dynamic panel model to find the determinants of resilience. It is interesting to notice that resilience measurement and the search for household's resilience determinants are here handled in two different phases.

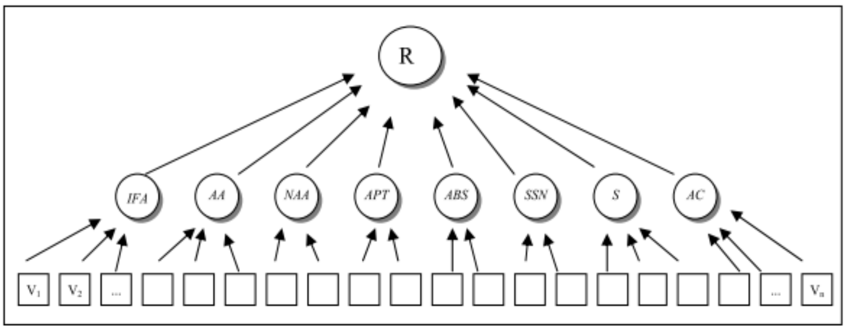
In this sense, this study is similar to Keil *et al*. (2008). The latter one deals with the resilience of Indonesian farmers towards ENSO-related drought. Here resilience is measured as "the observed degree of drought-induced expenditure reductions for basic necessities" (Keil *et*

[2] The advantage of this approach to resilience measurement is its flexibility and adaptability to various scenarios: in fact in the first stage we can include different variables according to the needs of the specific case study.

al., 2008: 294).[3] The absolute value of negative variations is supposed to be negatively correlated with resilience: a fully resilient household is expected to record null variations of basic consumption. The variables describing basic consumption are aggregated by using PCA. The first principal component is extracted and used to compute the scores. The next step is the specification of a model to identify the determinants of resilience.

Carter *et al*. (2006) apply their approach to the assessment of the impact of the 1998-1999 drought in Ethiopia as well as to the impact of the Mitch hurricane in Honduras in 1998. Their approach is based on the idea that resilient households have the ability and the possibility to smooth their consumption by depleting their asset stock or by implementing other coping strategies. Conversely, non-resilient households tend to cope by reducing their consumption in order to maintain their assets. Moreover the authors emphasize the existence of poverty traps: if a household' assets basket falls under a given threshold, the household is likely to not be able to recover from the shock.

In conclusion, using a proxy-based strategy is the most straightforward approach to measure resilience. The problem with this approach is the loss of complexity implied by the need of finding a single variable to approximate a complex phenomenon such as resilience.[4] Another issue is keeping separate the stage of resilience measurement from the identification of resilience determinants. If this is the adopted strategy, the distinction between resilience determinants and resilience observable onsets needs to be rigorously justified and consistent with a theoretical model. For these reasons we decided to adopt Alinovi *et al*.'s approach building on its flexibility to adapt to very different real cases. Indeed, in the first stage different variables can be included according to the needs of the specific case study (Figure 1).



Source: Alinovi *et al.* (2010)

Figure 1. Household Resilience Index Estimation Procedure

[3] It is interesting to notice that this definition is very close to the one adopted in the approach to vulnerability as uninsured risk (Quisquimbing and Skoufias, 2003), i.e. according to this approach resilience is actually the flip side of vulnerability.

[4] For example, though households' capacity to smooth their consumption is surely related to resilience, the latter is a complex concept encompassing more than just consumption smoothing.

2.3. Estimation Strategy

The two crucial features of resilience analysis are the acknowledgement of the dynamic nature of food systems (path dependency, discontinuous changes) and the heterogeneity in the mechanisms that allow people to earn their own living (the existence of multiple equilibria, non-linearity).[5] These two features call for an analytical framework that explicitly incorporates them. In terms of estimation strategy, the natural candidate to this analysis is the use of panel data at household level that allow the econometric estimation of fixed-effects estimators and dynamic estimators.

Let y_{it} be an index of the i-th household resilience to food insecurity at time t. Ideally, this index should indicate attainments of households outcomes such as nutritional status, health status, etc. This index is a function of a vector of observed time-varying covariates $\mathbf{x}_{it}$ including the household income level, asset endowments, access to basic services, social safety nets, etc., and depends also on a vector $\mathbf{z}_i$ of observed time-unvarying household or group-specific variables, such as ethnic group, sex composition, age structure, location, or unobserved household specific characteristics, such as heterogeneity in skills and preferences, while λ_t represents the time effect:

$$y_{it} = \alpha + \lambda_t + \mathbf{z}_i'\gamma + \mathbf{x}_{it}'\beta + \varepsilon_{it}. \tag{1}$$

If $\mathbf{z}_i$ can be observed for all households, the entire model can be treated as an ordinary linear model and fit by least squares. If $\mathbf{z}_i$ is unobserved, the model will be a fixed effect or a random effect model according to the different hypotheses on its correlation with $\mathbf{x}_{it}$.

Unfortunately, in most of developing countries, it is very difficult to have a suitable dataset that allows for this estimation strategy. The major limitations are the number of periods over which the cross-sections are observed and the comparability of the values assumed by the resilience index y_{it} over time.[6]

[5] As a result, the process of estimating resilience should reckon this and be different according to the different livelihood strategies adopted by each group (or, at least, according to groups of similar livelihood strategies).

[6] In fact, the dependent variable y_{it} is an index estimated over a multi-dimensional set of variables, different from the ones included in the two vectors $\mathbf{x}$ and $\mathbf{z}$, whose specific values need to be normalized to be summed up into a single index.

3. The Case Study: The Impact of Hurricane Mitch on Rural Household in Nicaragua

3.1. Dataset

Luckily enough the Nicaragua dataset makes possible addressing both dynamics and heterogeneity. It was based on three surveys. The first two surveys are the 1998 and 2001 *Encuesta nacional de hogares sobre medición de niveles de vida* (EMNV) that are nationally representative samples that can be combined to build a panel dataset of 3,078 households interviewed in both years. Hurricane Mitch hit Nicaragua right after the end of 1998 survey data collection.[7] In 1999 INEC decided to re-interview 540 household living in Mitch affected areas including in the questionnaire also questions aiming at assessing the impact of hurricane Mitch on the interviewed households.

In order to compute meaningful and comparable resilience indexes, the estimate should be carried out for socio-economic groups showing the same (or at least similar) process of resilience building.[8] This is why we decided to focus on agricultural households only,[9] that resulted in a sample size is 1,202 households. For these households we computed the resilience index according to a modified version of Alinovi *et al.* (2010) approach and then separately for different livelihood groups, identified using cluster analysis.

3.2. Identification of Livelihood Strategies

The classification of agricultural households into different livelihood groups has been implemented following the methodology used by Alinovi *et al.* (2010), which is using Euclidean distance and Ward's linkage algorithm to identify livelihood strategy clusters. The variables used to identify the livelihood strategies are: the sector of employment, job typology, income shares (i.e. from agricultural and non-agricultural activities), income sources (number of sector of employment in the household, share of household members not working in agriculture, share of members working as agricultural unskilled wage workers, share of household members who are inactive or unemployed), agricultural productive assets, and market reliance (share of self-consumption to agricultural output).

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[7] Hurricane Mitch hit Central America between 26th October and 4th November 1998 and is considered as one of the worst ever. It affected 12% Nicaraguan health structures and deeply damaged the infrastructural network in 70 out of 147 municipalities (USAID, 1999). Mitch impact was impressive with losses ranging from 7% to more than 60% of the impacted crops (ECLAC, 1999).

[8] Indeed, looking for a resilience model linking risks, ex ante protections and ex post responses needs to explicitly acknowledge the variety and specificity of people's way to gain their own livelihood. As a result, the estimation of statistical models, which necessarily identify average behaviors, can be only performed separately per each livelihood strategy to prevent blurring the estimation exercise.

[9] Poverty in Nicaragua is a widespread phenomenon: the poverty head count ratio, measured according to the national poverty line, decreased only marginally from 50.3% in 1993 to 48.3% in 2005 (IMF, 2010), with poverty in rural areas being twice as much than in urban areas and higher incidence in the Central and Atlantic districts.

The analysis identifies four agricultural livelihood strategies, namely (Table 1):

- *agricultural wage earners*: this group features the lowest share of income from agriculture (on average 76%); about one third of household heads work as agricultural unskilled wage worker; most households are net food buyer and about 40% of them live in urban areas; this group more likely diversifies between agricultural and not agricultural activities;
- *minifundia owners*: these households are on average endowed with 2 ha of land and with a very poor stock of capital and livestock; about one half of them is net food buyer; more than 84% of income is from agriculture;
- *small-medium landowners*: the average farm size is 16 ha and capital endowment is quite important;[10] the share of non-agricultural income is very low (about 5%) while livestock plays an important role;

Table 1. Average value of relevant variables according to livelihood groups

Variables	Total HHs	s.d.	Wage earners	Minifundia	Medium size own.	Large owners
number of hh	1,237	-	373	479	342	43
Sector of Employment						
hh head in agriculture	0.702	0.420	0.493	0.770	0.822	0.884
hh head in secondary sector	0.037	0.175	0.056	0.029	0.023	0.047
hh head in commerce	0.045	0.153	0.113	0.019	0.009	0.000
hh head not working	0.114	0.301	0.188	0.090	0.082	0.000
hh head inactive	0.065	0.218	0.088	0.065	0.041	0.047
Job Classification						
hh head peon	0.170	0.385	0.314	0.148	0.064	0.023
Income Shares						
sh. of income from agriculture	0.822	0.220	0.763	0.844	0.850	0.894
sh. of income from agricultural wages	0.290	0.371	0.580	0.220	0.094	0.045
sh. of income from crop	0.290	0.347	0.056	0.424	0.355	0.348
sh. of income from livestock	0.227	0.303	0.119	0.180	0.384	0.501
sh. of income from land rent	0.029	0.153	0.016	0.041	0.030	0.000
sh. of income from non agr. activities	0.085	0.158	0.124	0.074	0.055	0.086
Income Sources						
number of sector of employment	1.213	0.517	1.260	1.182	1.208	1.163
sh. of working members not in agriculture	0.084	0.137	0.151	0.056	0.057	0.035
sh. of members in agriculture	0.322	0.236	0.240	0.344	0.373	0.397
sh. of members peones	0.180	0.215	0.168	0.184	0.188	0.195
sh. of members unemployed or inactive	0.593	0.242	0.609	0.600	0.569	0.567
Agricultural Assets						
livestock (TLU)	2.678	10.161	0.006	0.911	4.883	28.636
agricultural capital	3,729	22,694	2	335	7462	46,252
land (ha)	12	49	0	2	16	187
extra hh labour (C$)	6,580	49,961	1	968	5,030	145,964
Market Reliance						
share of self-consumption	0.274	0.266	0.033	0.445	0.305	0.178
net food buyer	0.583	0.499	0.997	0.501	0.307	0.070

[10] The small-medium farmers average land size is about eight times that of *minifundistas*, while their capital endowment is more than twenty times higher.

- *large owners*: these households own 187 ha land on average; capital endowment, extra household labour demand and livestock are remarkable; about one half of total income is from livestock.

3.3. Resilience Index Estimation

The resilience to food insecurity of a given household at a given point in time is assumed to depend primarily on the options available to that household to make a living, such as its income-generating activities, access to assets, basic services and social safety nets, adaptive capacity, etc.:

$$R_i = f\left(I_i, ABS_i, AA_i, NAA_i, TL_i, SSN_i, AC_i, PC_i, EC_i, HHD_i\right). \qquad (2)$$

In this framework, resilience is not observable *per se* and is considered a latent variable depending on the terms on the right-hand side of equation (2). To estimate *R*, it is therefore necessary to estimate separately the household income (*I*), access to basic services (*ABS*), agricultural assets (*AA)*, non-agricultural assets (*NAA*), production technological level (*TL*), social safety nets (*SSN)*, adaptive capacity (*AC*), physical connectivity (*PC*), economic connectivity (*EC*) and some household demographic characteristics (*HHD*)*,* which are themselves latent variables because they cannot be directly observed in a survey, although it is possible to estimate them through multivariate techniques (Table 2).

Table 2. Composition of the Agricultural Resilience Index

Income	Access to Basic Services	Agr. Assets	Non Agric. Assets	HH. Tech. Level	Social Safety Nets (1)	Social Safety Nets (2)	Adaptive Capacity	Physical Connectivity	Economic Connectivity	HH Demographics
per capita income	distance to school	land	durables	prod. capital	institutional transfers	private transfers	n employed	access to the household (kind of road)	market reliance for food	dependency ratio
	safe water	capital	house				n sectors of employment	tv	access to credit	
	distance to water	livestock					education hh head	ownership of private transportation mean	financial assets	
	distance to health facility						max education in hh			
	safe sewage						empl. ratio			
	electricity						health insurance			

Thus, the resilience index is estimated using a two-stage factor analysis strategy (Figure 1). In the first stage, an index for each component is estimated separately using an iterated principal factor method over a set of observed variables (Annex 2). In the second stage, the resilience index is derived using a factor analysis on the interacting components estimated in the first stage, in which the resilience index is a weighted sum of the factors generated using Bartlett's (1937) scoring method and the weights are the proportions of variance explained by each factor.

Table 3 shows the factor loadings of the agricultural resilience index whose signs are all positive as expected.

Table 3. Factor loadings of the resilience dimensions

Resilience Dimension	Factor Loadings
Income	0.197
Access to Basic Services	0.488
Agricultural Assets	0.622
Non-agricultural Assets	0.518
HH Production technological level	0.545
Public transfers	0.112
Private transfers	0.104
Adaptive capacity	0.526
Physical connectivity	0.705
Economic Connectivity	0.385
HH demographics	0.240

Large owners are by far the better-off group while *minifundia* owners have the lowest resilience value (Figure 2). Small-medium land owners and wage workers show similar level of resilience although the value of the small-medium land owners is slightly higher. The western regions (Managua, Northern and Southern Pacific Coast) seems to be much more resilient than the central and eastern regions (Figure 3), with Managua and the Atlantic Coast ranking as the better off and the worse off, respectively.

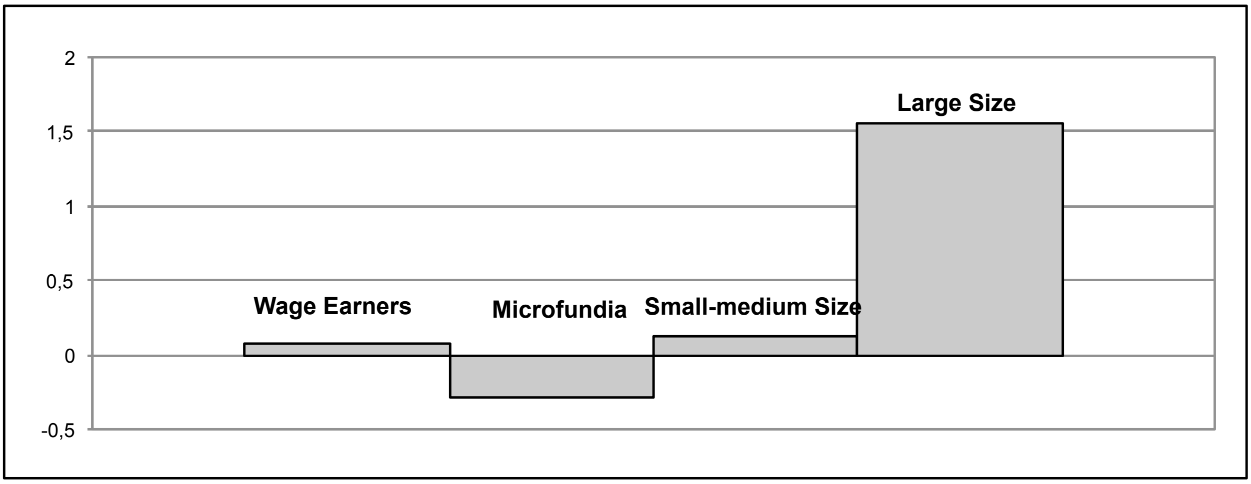

Figure 2. Average resilience level per livelihood groups

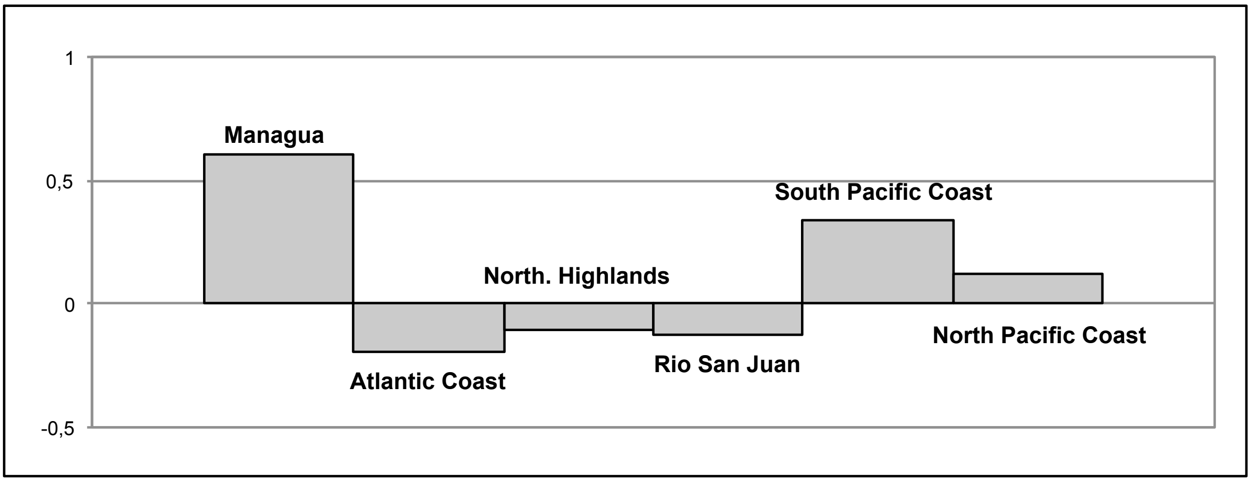

Figure 3. Average resilience level per geographic areas

It is interesting to go beyond averages, analysing the contribution of each dimension to resilience per livelihood group. The radar graphs in Figure 4 provide a useful tool to give a snapshot of the situation in each livelihood group. Medium-small size farmers show high values of agricultural and non-agricultural assets as well as a high level of productive capital and of income and access to food. Wage-workers have very low level of agricultural assets and of agricultural productive capital while their adaptive capacity and physical connectivity is quite high[11]. The situation of *minifundia* owners is particularly concerning: they are constrained by their scarce land endowment and are less able to diversify among sectors than wage earners. At the same time, the low amount of agricultural assets, non-agricultural assets and production capital does not allow these households to have enough buffer capacity in case of shocks (Davis and Stampini, 2002). Furthermore, capital and asset endowment of *minifundia* owners is not only lower but qualitatively different from the one of small-middle size farmers, being much less capital-intensive. Moreover agricultural production is based mostly on crop production meaning that *minifundia* households cannot exploit livestock farming in its double role of source of income and asset accumulation. The high value of *minifundia* owners' private transfer dimension highlights their high reliance on traditional and non-governmental safety nets. Not surprisingly large owners show very high levels of agricultural and non-agricultural assets as well as production capital.

[11] Indeed, wage-workers are more likely to live in urban areas and more able to diversify between sectors.

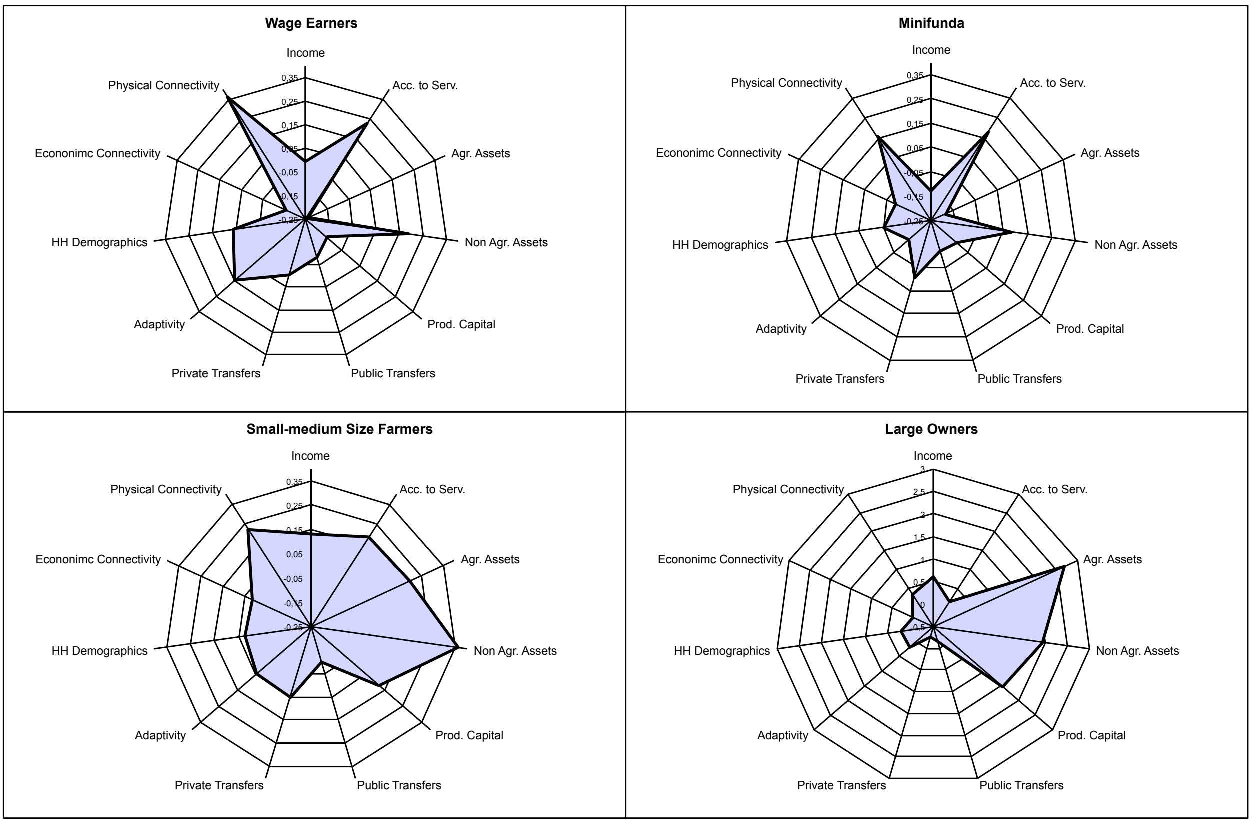

Figure 4. Resilience Determinants per Livelihood Groups

3.4. Resilience Index Validation

The most important research question we address here is whether the construct we are measuring, i.e. resilience, is relevant for predicting future well-being attainments (in our case food security). Nicaraguan EMNV 1998, 1999 and 2001 surveys offer a good base to test the validity of the resilience index. In fact, 1,221 agricultural households have been sampled both in 1998 and in 2001; among these households, 258 were affected by hurricane Mitch in 1998 and interviewed in the 1999 survey.

Table 4 reports a summary of food poverty dynamics between 1998 and 2001 in the selected sample[12]. There was a slight decline in food poverty in the sample between 1998 and 2001 resulting from a positive balance of movements in and out from poverty (203 vs. 187). Being food poor is a much more unstable condition than being non food poor: about 40.68% of 1998 food poor experienced a transition out of poverty between 1998 and 2001; vice versa only 25.90% of 1998 non food poor became food poor in 2001.

[12] Food poverty has been identified according to an extreme poverty line set equal to the annual cost to buy a basket of food that provides 2,187 Kcal per person per day. The two resulting poverty lines were C$2,489 and C$2,691 in 1998 and 2001 respectively (World Bank, 2003).

Table 4. Food Poverty Dynamics in Nicaragua, 1998 - 2001

		2001		
		Food Poor	**Non Food Poor**	**Total**
1998	**Food Poor**	296 (24.24%)	203 (16.63%)	499 (40.87%)
	Non Food Poor	187 (15.32%)	535 (43.82%)	722 (59.13%)
	Total	483 (39.56%)	738 (60.44%)	1,221 (100.00%)

The general idea behind the model is the following: at time *t* each household is characterized by a number of characteristics that contribute to the definition of its livelihood strategy, its food security attainment and its level of resilience. Between *t* and *t* + 1 the household may be hit by some shocks. The level of food security at time *t* + 1 is given by the interaction between the three components above, namely livelihood strategies and resilience, which determine the household ability to cope with shocks, and the shocks experienced by the household. This framework is formalized as follows:

$$\Delta FCpc_{(h,t|t+1)} = \alpha R_{h,t} + FCpc_{h,t} + \sum_{i=1}^{k} \gamma_i LIV_{h,t} + \delta \sum_{i=1}^{k} \xi_i S(i)_{(h,t|t+1)} + \mu X_h + \varphi Z_{h,t} + \varepsilon_{h,t} \qquad (3)$$

where the dependent variable, $\Delta FCpc_{(h,t|t+1)}$, is the difference between log food expenditure between 1998 and 2001, i.e. the rate of growth of food expenditure in the period taken into consideration,[13] $R_{h,t}$ is household *h*'s resilience at time *t*, X_h and $Z_{h,t}$ are respectively time invariant and time varying household characteristics, $LIV_{h,t}$ is a variable that indicates the livelihood strategy adopted by the household at time *t*, *S* is a vector of shocks occurred between *t* and *t* + 1, $\varepsilon_{h,t}$ is a stochastic error term.

Some descriptive statistics of the variables included in the model are reported in Table 5.

[13] The most appropriate outcome variable is probably caloric intake per capita computed using equivalence scale to avoid the bias due to differences in household composition. However, the distribution of such variable in the Nicaragua dataset shows extremely low and high values in the two tails of the distribution (particularly in the right hand one) that raise doubts on the reliability of this variable. Therefore, we decided to use as dependent variable the food expenditure per adult equivalent, and its change between 1998 and 2001, in real terms (i.e. deflated by using the consumer price index).

Table 5. Descriptive statistics of the variables included in the model

Variable	Kind of Variable	Mean	Standard Deviation
log Food expenditure 1998	continuous	7.742	0.67
Food poor 1998	binary	0.396	0.489
Food poor 2001	binary	0.409	0.492
Into food poverty	binary	0.153	0.360
Out of food poverty	binary	0.166	0.372
Shocks			
Natural shocks	binary	0.513	0.554
Anthropic shocks	binary	0.559	0.604
Hurricane Mitch	binary	0.211	0.408
Region of Residence			
Region: Managua	binary	0.025	0.157
Region: Atlántico	binary	0.146	0.353
Region: Northern Highlands	binary	0.39	0.488
Region: Rio San Juan	binary	0.139	0.346
Region: South Pacific Coast	binary	0.159	0.366
Region: North Pacific Coast	binary	0.141	0.348
Area of Residence			
Urban	binary	1.793	0.405
Livelihood Group			
Large owners	binary	0.297	0.457
Wage earners	binary	0.393	0.489
Minifundia owners	binary	0.275	0.447
Small-middle size farm owners	binary	0.034	0.182
Resilience			
Resilience index		0	1.005
Resilience: 4th quart.	binary	0.25	0.433
Resilience: 3rd quart.	binary	0.25	0.433
Resilience: 2nd quart.	binary	0.25	0.433
Resilience: 1st quart.	binary	0.251	0.434
HH Head Characteristics			
HH head is white	binary	0.144	0.351
HH head is male	binary	0.174	0.38

"Into poverty" and "Out of poverty" are two dummy variables equal to one if the household became food poor or moved out from food poverty between 1998 or 2001. "Natural Shock" and "Anthrophic Shocks" are two dummy variables equal to 1 if the household has been exposed to natural (e.g. floods, droughts, pest etc.) and "anthropic" (e.g. robbery, rustling, extortions, direct violence) shocks respectively. The model includes a set of dummies describing the region of residence with Atlántico considered as reference category. Another set of dummies describes the livelihood strategy group the household belongs to, "Large Owners" being the reference category. Resilience is included in the model through a set of dummies indicating the quartile the household belongs to in the distribution of the resilience index: the 4^{th} quartile is the reference category. "HH head is white" is a binary variable equal to 1 if the head of the household is white in contrast with coloured, native and *mestizos*.

All the variables but the change in food expenditure and the value of the resilience index are binary variables while the dependent variable is continuous. In such a situation the presence of heteroskedasticity is very likely (Grizzle *et al*., 1969).[14] In other words, we know that ordinary least squares (OLS) estimates will likely be biased as the assumption of constant variance of the disturbances might not hold; at the same time we have also some priors on the variables that are likely to influence disturbances. This suggests an estimation strategy for dealing with heteroskedasticity. In fact, once verified that OLS estimates are biased because of heteroskedasticity[15] the estimation strategy is articulated in four steps:

- estimation of the fitted error term of the OLS regression
- specification of a functional form of ε_i (to estimate a s.d. function) or of ε_i^2 (to estimate of a variance function).[16] It is possible to regress ε_i or ε_i^2 on a subset of the independent variables used in the OLS regression or on the fitted values of the dependent variable. At the end the most general specification (the regression of $|\varepsilon_i|$ on all the dependent variables);
- the fitted value of the previous step regression (v_i or s_i) can be used to compute the weights to be used in the weighted least squares (WLS) or variance-WLS regression.[17]

The estimates of the best models are reported in Table 6. Food expenditure growth is slower for households showing a higher initial level of expenditure. Households exposed to natural and anthrophic shocks present a slower growth of food expenditure (though these variables are not significant only in the WLS model). As expected, household exposed to hurricane Mitch presents a lower food expenditure growth rate. Resilience is a very good predictor of food expenditure rate of growth in both models. All the coefficients show that belonging to lower quartiles of resilience distribution is systematically linked to a lower food expenditure growth rate. Moreover the significance of resilience is very robust to changes in model specification.[18]

[14] The likelihood of heteroskedasticity is increased by the method adopted to identify groups in the cluster analysis, namely the Ward's Linkage method, which identifies groups by minimizing the variance within groups and maximizing variance between groups: this method implies that groups aggregated at an earlier stage of the regression tree have a lower within group variance than other groups.

[15] This can be done through a Breusch-Pagan test (Breusch and Pagan, 1979). The value of the test is 0.66 with a p-value of 0.418 suggesting the rejection of the null hypothesis of homoskedasticity at any conventional level of confidence.

[16] Many specifications have been tested and, provided that the livelihood groups dummies are included, there are no significant differences among specifications.

[17] In WLS the magnitude of the error variance is estimated during the regression as the inverse of v_i. In VWLS the error variance is not estimated by the regression: s_i is considered the true standard deviation of the observation and is used to compute the coefficient standard errors.

[18] Resilience is significant even if included in the model as continuous variable.

Table 6. Model Estimates (Food Expenditure)

Dep. Var.: Diff. Log. Food Exp.						
Variable	**WLS**			**VWLS**		
	Coeff.	**S.E.**		**Coeff.**	**S.E.**	
log Food expenditure 1998	-0.127	0.016	***	-0.123	0.011	***
Shocks						
Natural shocks	-0.030	0.021		-0.025	0.014	*
Anthropic shocks	-0.032	0.020		-0.034	0.013	**
Hurricane Mitch	-0.060	0.034	*	-0.066	0.023	**
Region of Residence						
Region: Managua	-0.016	0.071		0.007	0.049	
Region: North. Highlands	-0.039	0.032		-0.031	0.021	*
Region: Rio San Juan	0.028	0.039		0.030	0.026	
Region: South Pacific Coast	0.017	0.040		0.019	0.026	
Region: North Pacific Coast	0.014	0.040		0.016	0.027	
Area of Residence						
Urban	0.031	0.029		0.043	0.019	
Livelihood Group						
Wage earners	-0.127	0.060	**	-0.124	0.060	***
Minifundia owners	-0.119	0.059	**	-0.124	0.059	***
Small-middle size farm owners	-0.109	0.059	*	-0.112	0.059	***
Resilience Quartile						
Resilience: 3rd quart.	-0.102	0.032	***	-0.104	0.022	***
Resilience: 2nd quart.	-0.126	0.033	***	-0.127	0.022	***
Resilience: 1st quart.	-0.243	0.034	***	-0.234	0.023	***
Interact. Term Mitch*Food Exp.						
Interaction: 3rd quart.*Mitch	0.172	0.074		0.112	0.045	*
Interaction: 2nd quart.*Mitch	-0.031	0.067		-0.016	0.044	
Interaction: 1st quart.*Mitch	0.172	0.074	**	0.186	0.048	***
HH Head Characteristics						
HH head is white	-0.006	0.030	*	-0.003	0.020	*
HH head is male	0.050	0.027	*	0.056	0.021	***
Constant	1.506	0.153	**	1.446	0.113	**
obs. 1,221	**Adj. Rq.=**0.095			**GoF=** 2439.04 **Prob>Chi2** 0.000		
	F-Stat= 5.78	**Prob>F=**0.000		**M. Chi2=**247.72	**Prob>Chi2** 0.000	

*, **, ***: significant at the 10, 5 and 1 per cent respectively.

The most important result is the validation of the resilience index as predictor of well-being attainments: the higher the resilience measured at time *t*, the higher the household level of food security at time $t + 1$ all other things being equal. The interaction term between Mitch exposure and the first quartile of food expenditure is positive and significant: the interpretation of this result can be that households characterized by low initial level of food expenditure are not likely to further cut their level of food consumption. The role played by the region of residence is on the whole not significant. As expected, households belonging to the large owners livelihood group have a systematically higher food expenditure growth rate, just as households headed by a male (even if this coefficient is barely significant in the WLS specification).

The same dataset can be also used to explore the relationship between resilience and vulnerability. Operationally, this can be done testing the relationship between resilience at time t (i.e. in 1998) and the probability of being food poor at time $t + 1$ (i.e. in 2001). This model has been estimated using a logit specification, with a dummy describing food poverty status in 2001 as dependent variable. The marginal effects at the mean estimates and heteroskedasticity robust standard errors are reported in Table 7.

Table 7. Model Estimates (Food Poverty)

Dep. Var.: Food Poor 2001			
Variables	**Coefficient (dx/dy)**	**Robust S.E.**	
Food poor 1998	0.287	0.031	***
Shocks			
Natural shocks	-0.007	0.033	
Anthropic shocks	0.029	0.031	
Hurricane Mitch	-0.003	0.041	
Region of Residence			
Region: Managua	0.006	0.107	
Region: North. Highlands	0.196	0.050	***
Region: Rio San Juan	-0.132	0.052	**
Region: South Pacific Coast	0.003	0.062	
Region: North Pacific Coast	-0.032	0.061	
Area of Residence			
Urban	0.061	0.044	
Livelihood Group			
Wage earners	0.169	0.124	
Minifundia owners	0.245	0.117	**
Small-middle size farm owners	0.146	0.124	
Resilience Quartile			
Resilience: 3rd quart.	0.302	0.050	***
Resilience: 2nd quart.	0.191	0.049	***
Resilience: 1st quart.	0.146	0.049	***
HH Head Characteristics			
HH head is white	0.137	0.045	***
HH head is male	-0.008	0.040	
obs. 1,211			
Wald Chi2=222.51 **Prob>chi2=**0.000 **Pseudo R2=**0.179			

*, **, ***: significant at the 10, 5 and 1 per cent respectively.

The model highlights a significant path dependency effect of food poverty: being food poor in 1998 increases the probability of being food poor in 2001 by 28.7%. The effect of shocks is not significant in this specification, while living in the Northern Highland region and in Rio San Juan changes the probability of being food poor respectively by 19.6% and -13.2%. The model confirms the difficulties of *minifundia* owners who have an higher probability of being poor 2001 (+24.5%). Resilience is highly significant and the probability of being food poor at $t + 1$ is higher for lower quartiles of resilience: this result confirms again the reliability of the resilience index as a predictor of food insecurity. Households whose household head is white are unexpectedly more prone to be food poor in 2001.

Another interesting issue is the transition from poverty to non-poverty and vice versa estimating a model considering only the households who were not food poor in 1998, i.e. 722 observations. Here is interesting to identify the determinants of this dynamics and among them the role played by resilience (Table 8).

Table 8. Model Estimates (Transition to Food Poverty)

Dep. Var.: Into Food Poverty			
Variables	**Coefficient (dx/dy)**	**S.E. (Robust)**	
Shocks			
Natural shocks	-0.027	0.033	
Anthropic shocks	0.031	0.030	
Hurricane Mitch	0.005	0.043	
Region of Residence			
Region: Managua	-0.070	0.097	
Region: North. Highlands	0.144	0.058	**
Region: Rio San Juan	-0.113	0.047	**
Region: South Pacific Coast	0.014	0.069	
Region: North Pacific Coast	-0.089	0.054	*
Area of Residence			
Urban	0.092	0.051	*
Livelihood Group			
Wage earners	0.021	0.104	*
Minifundia owners	0.156	0.117	
Small-middle size farm owners	0.002	0.101	
Resilience Quartile			
Resilience: 3rd quart.	0.151	0.055	***
Resilience: 2nd quart.	0.185	0.061	***
Resilience: 1st quart.	0.264	0.070	***
HH Head Characteristics			
HH head is white	0.077	0.049	
HH head is male	0.023	0.048	
obs. 722			
Wald Chi2=109.95 **Prob>chi2=**0.000 **Pseudo R2=**0.153			

*, **, ***: significant at the 10, 5 and 1 per cent respectively.

Living in the Northern Highlands region increase the transition probability by 14.4% while to live in Rio San Juan and in North Pacific Coast has an opposite effect (respectively -11.3% and -8.9%). Live in urban areas is surprisingly related to a higher transition probability. Wage earners present systematically higher transition probability, though the coefficient is barely significant. Again, resilience is highly significant and the lower the resilience quartile the higher the probability of experiencing a transition to food poverty. In conclusion, the transition to food poverty is much more influenced by household's resilience than by household's livelihood strategies.

Table 9 reports the estimates of the transition out from food poverty. In this model the subsample includes only households who were classified as food poor in 1998, i.e. 499 observations.

Table 9. Model Estimates (transition out of food poverty)

Dep. Var.: Out of Food Poverty			
Variables	**Coefficient (dx/dy)**	**S.E. (Robust)**	
Shocks			
Natural shocks	-0.028	0.053	
Anthrophic shocks	-0.025	0.048	
Hurricane Mitch	0.031	0.060	
Region of Residence			
Region: Managua	-0.267	0.127	**
Region: North. Highlands	-0.171	0.066	**
Region: Rio San Juan	0.141	0.091	
Region: South Pacific Coast	0.026	0.085	
Region: North Pacific Coast	-0.059	0.086	
Area of Residence			
Urban	-0.001	0.0660	
Livelihood Group			
Wage earners	-0.355	0.124	***
Minifundia owners	-0.366	0.148	**
Small-middle size farm owners	-0.313	0.113	***
Resilience Quartile			
Resilience: 3rd quart.	-0.076	0.074	
Resilience: 2nd quart.	-0.130	0.070	**
Resilience: 1st quart.	-0.250	0.066	***
HH Head Features			
HH head is white	-0.212	0.060	***
HH head is male	0.041	0.058	
obs. 499			
Wald Chi2=53.72	**Prob>chi2=**0.000	**Pseudo R2=**0.084	

*, **, ***: significant at the 10, 5 and 1 per cent respectively.

The crucial role played by resilience is confirmed in this model too with a probability of transition significantly lower for households belonging to the first and second resilience quartile. Managua and Northern Highlands shows a systematically lower transition probability.[19] All livelihood groups other than large owners present a lower transition probability if compared to large owners, although small-medium owners show a slightly higher coefficient than wage earners and *microfundia* owners. In this model too, household with a white household head shows a worse performance, with a lower probability of transition out from poverty (21%).

[19] The result for Managua is quite unexpected but it is affected by the facts that only five households living in Managua are included in that sample.

3.5. Impact Evaluation of Resilience-enhancing Interventions

The evaluation of the impact of policies is a crucial issue for both scholars and policy makers, being the assessment of policy effectiveness is important not only to improve the design of future interventions, but also ensure accountability to donors and taxpayers. The focus here is on if and how the impact of a given policy intervention on household's resilience can be assessed. In fact a shock is likely to reduce household's resilience and consequently to increase household's vulnerability to future shocks; therefore measuring the policy impact on resilience can improve future policy design.

Our case study focuses on households hit by hurricane Mitch and it is aimed at evaluating the impact of rehabilitation and relief measures implemented in the post-Mitch years on households' resilience. The problem of counterfactual (Khandker *et al*., 2010) in this case is even more tricky than usual as the outcome variable is not observable. To identify an appropriate counterfactual we used propensity score matching[20], which uses observed households characteristics to match treated and not treated units. Once observations are matched, the average treatment effect can be computed and it will be possible to test if it is significantly different from zero.

Nicaraguan households exposed to hurricane Mitch have been targeted by several relief and rehabilitation programs (Table 10) aimed at mitigating the negative effects of Mitch on agriculture production and household assets.

Table 10. Household Participation to Post-Mitch Programmes

Interventions	Households	%
assistance to agricultural firm	18	3.03
technical assistance	30	7.11
transfer	311	52.27
assets	77	12.94
infrastructure	190	31.92
in kind	297	49.92
support to production	283	47.56

The impact of these policy measures on household resilience has been checked through PSM using N-N matching (Becker and Ichino, 2002). In order to have a larger sample size, also households with at least a half of labour force in agriculture have been included, while the threshold of agricultural income percentage has been reduced to 20%. As a result the sample size is 1,367 households, 278 of them affected by Mitch.

[20] Propensity score matching works provided that there are no unobserved characteristics affecting participation and treated and not treated have fairly similar propensity scores (Heckman *et al.*, 1999).

The only policy measure showing a significant impact on resilience is the participation to assets provision programs. Table 11 reports the results of the selection equation. Despite the likelihood ratio test rejects the hypothesis of all coefficients being zero, the estimates are not very meaningful. The balance test excludes balance problems. The average treatment for treated is about 10% and is significant only at 10%. Given the low number of observations these results may be considered satisfactory.

Table 11. Household Participation to Asset Programs

Dep. Var.: Asset Program			
Variables	**Coeff.**	**Robust S.E.**	
Urban	0.55053	0.298065	*
Region: North. Highlands	0.36215	0.404741	
Region: Rio San Juan	0.19024	0.531679	
Region: South Pacific Coast	-0.01015	0.528455	
Region: North Pacific Coast	0.86634	0.397004	**
Agricultural Damage	0.16504	0.228697	
House Damage	-0.14592	0.192801	
Resilience 1998	-0.04477	0.143523	
Constant	-2.64285	0.621601	***
obs. 278			
Wald Chi2=22.47	**Prob>chi2** 0.002	**Pseudo R2=**0.083	

Despite the limited meaning of this exercise, the crucial role played by assets in enhancing household's resilience is here confirmed particularly in such a post-shock scenario. As expected the impact on resilience of programs concerning cash and in kind transfers is not significant: these programs are in fact aimed to emergency relief. We would have expected to find a significant impact of other programs (such as technical assistance, infrastructures etc.), but this does not seem to be the case. However, given the small sample size, we should be very cautious in drawing policy implications: here we are more interested in showing the feasibility of the methodology rather than focus on the reliability of results.

4. Conclusions

Building on Dercon (2001) we argue that vulnerability is function of the risks faced by households as well as household resilience to those risks, which in turn depends on the options available to the household to make a living and on its ability to handle risks. These hypotheses have been tested in the empirical application to Nicaragua and the impact of Mitch hurricane in a dynamic specification modeling, addressing the following questions: (i) how can household resilience to food insecurity be measured? (ii) does household resilience contribute to ensuring household food security? (iii) how can household resilience be used to evaluate the impact of policy measures.

The basic problem concerning resilience measurement is that resilience is not directly observable. We proposed a revised version of the multivariate analysis approach originally proposed by Alinovi *et al*. (2008 and 2010) which models resilience as a latent variable. The most important innovations here are: (i) dropping shocks as determinants of resilience (ii) including economic, physical and social connectivity and (iii) including some household characteristics, which are important determinants of the household livelihood strategy. We developed also a dynamic specification of household food security that made possible to validate the measurement approach through empirically testing the second research question above. Our results prove that the resilience index is consistently the most robust predictor of household food security irrespective of the adopted specification. All other things equal, being more resilient at time t is strongly and positively related with the level of food security at time $t + 1$ and with the probability of escaping food poverty between t and $t + 1$; at the same time, being less resilient at t is positively related with the probability of being food poor in at time $t + 1$, and with the probability of a transition from being not food poor to being food poor between t and $t + 1$.

The reliability of our results is supported by the resilience profiling emerging from our estimates, which is able to summarize the most relevant issues concerning food security in rural Nicaragua and is consistent with previous results of other studies, which identifies *minifundistas* and agricultural wage earners as the least resilient groups. Even more interesting is the evidence that the combination of reliance on agriculture and of a low endowments of assets tends to lower household's ability to manage shocks: the issue of access to agricultural assets, primarily to land, is crucial for household resilience to food insecurity.

A huge shock such as hurricane Mitch is likely to undermine household resilience to future shocks: agricultural and non-agricultural assets may be destroyed, the infrastructural endowment may be damaged, household labour force endowments may be reduced, etc. Post-shock interventions are usually, and rightly so, focused on the immediate needs of the affected population. However, once immediate needs have been fulfilled and minimum standard of livelihoods secured, households' resilience reconstitution should be an overriding goal of policy interventions. Despite significant data limitations, we test the impact of post-Mitch policy measures on Mitch affected household and found a positive impact of assets reconstitution programs on households' resilience. Besides the specific result, it is important that coupling standard policy evaluation techniques with resilience analysis has proven to be feasible.

In terms of policy implications adopting resilience as a criterion for policy design means overcoming the usual dichotomy between emergency and development interventions. More generally, a resilience-based policy design means shifting policies from those that aspire to control change in systems assumed to be stable, to managing the capacity of social-ecological systems to cope with, adapt to, and shape change. However, the discussion above makes clear that resilience-based interventions are primarily eligible for: (i) non-emergency, business-as-usual contexts, (ii) after crisis, rehabilitation phase, or (iii) protracted crises contexts, that is whenever there is room for resilience management actions or interventions aiming at re-building resilience.

The major limitations of the proposed approach are in terms of data needs and comparability of results. In fact, the quantitative assessment we proposed is very demanding in terms of data: the development of a dynamic specification requires a panel dataset, and the level of detail for computing the resilience index is at least as much as the one of a living standard or an household income and expenditure survey. Furthermore, even if those data are available, a quantitative assessment cannot be carried out for the whole population, but only for similar livelihood strategy groups. As emerged in our case study, different livelihood groups have different strategies to gain their own livings, and imposing a single model for computing the resilience index across very different livelihood groups might lead to aberrant results.

There are three main areas for future developments in the field of resilience to food insecurity, namely: (i) merging quantitative and qualitative approaches; (ii) dealing not only with shocks but also with stresses; and (iii) up-scaling the quantitative at a more aggregated level (e.g. community).

The resilience assessment of a given food system can only partially be achieved through a synthetic indicator such as the proposed resilience index: understanding system dynamics, highlighting strategic issues, identifying and understanding strengths and weaknesses of the system may require both quantitative and qualitative knowledge. Therefore, it is very timely to explore the possibility of developing synergies between quantitative and qualitative approaches in order to have a comprehensive and effective toolbox.

Another interesting issue is how stresses can be included in the resilience assessment framework. In this study we dealt with hurricane Mitch, that is a single, strong shock. Stress on the contrary often is a business-as-usual condition for households, particularly in developing countries. Food systems' resilience may be challenged not by a single exceptional event, but by enduring phenomena – such as soil fertility losses due to climatic factors or to anthropic pressure – that constantly undermine livelihoods. This has huge implications on household behaviour, shaping households' livelihood strategies. Furthermore, from an estimation strategy viewpoint this phenomenon might imply endogeneity.

Lastly, the assumption made in most of the literature dealing with food security is that the household is the unit of analysis. Even though this assumption holds, it might be interesting to explore, how to measure resilience at higher levels of aggregation and in particular at community level (tribe, village, catchment). In fact there are several resilience dimensions such as access to basic services (heavily dependent on infrastructural endowment) or informal safety nets that are developed at the community level. Moreover individual belonging to the same community are likely to share similar climatic condition, a similar level of prices and similar unobserved community level characteristics (that are relevant from a computational point of view). Exploring the feasibility of appropriate techniques to model these features, such as multi-level methods, may prove fruitful.

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Annex 1. Empirical Approaches to Resilience Measurement

Author(s)	Alinovi *et al.* (2010) Alinovi *et al.* (2008)	Mulat and Negussie (2010)	Keil *et al.*(2008)	Carter *et al.* (2006)
Resilience Definition	Resilience as a latent variable based on severall pillars: (i) social safety nets, (ii) access to public services, (iii) assets, (iv) income and food access, (v) stability and (vi) adaptive capacity	Resilience considered as a latent variable based on (i) access to food, (ii) liquid assets (iii) education and (iv) social capital	Resilience defined as variation in basic consumption due to a shock	Resilience defined as households' incapacity of smooth their consumption by depleting their assets stock
Measurement Tecnique	Two Stage Factorial Analysis and CART	Principal Component Analysis	Principal Component Analysis	Livestock Assets
Separability of Measurement and Determinants Detection	NO	YES	YES	YES
Data Requirement	Cross Sectional Data	Panel Data (3 or more period to apply A-B estimator)	Panel and Recall Data	Panel Data
Model for Determinants Detection		Static and Dynamic Panel Model $\Delta R_{it} = \Delta R_{i,t-1}\varphi + \Delta x_{it}\beta + \Delta \mathrm{H}_{it}\gamma + \Delta\varepsilon_{it}$ $R_{it} = \alpha + X'_{it}\beta + H'_{it}\gamma + \varepsilon_{it}$	Tobit Model $\begin{cases} y_i^* = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \varepsilon_i \\ DRI_i = \min(y_i^*, 1) \end{cases}$	$\ln\left(\frac{A_{ri}}{A_{bi}}\right) = x_i\beta + \sum_{j=1}^{4}(Q_{si}^{j})\beta_A^j + $ $+ \sum_{j=1}^{4}\left[(Q_{bi}^{j}\Theta_i)\beta_\Theta^j + (Q_{bi}^{j}\Theta_i L_i)\partial_L^i + (Q_{bi}^{j}\Theta_i K_i)\delta_K^j\right] +$ $+ \varepsilon_i\beta_\varepsilon + F_i\delta_F + \omega_i$
Resilience to what?	General Resilience: to idiosyncratic and covariate shocks	General Resilience: to idiosyncratic and covariate shocks	Specific Covariate Shocks	Specific Continuative or Punctual Covariate Shocks

Annex 2. Description of Resilience Index Components and Factor Loadings Estimates

Income (I)

- *per capita income*: is the sum of all the available income sources to the household divided per adult equivalent.

Access to Basic Services (ABS):

- *health facility*: distance to the nearest health facility (measured in terms of time)
- *school*: distance from house and the nearest school; the distance is measured in time as households may have different means of transport;
- *water source*: distance (measured in terms of time) to the source of water usually accessed by the household for domestic use;
- *safe water*: dummy equal to one if the household has access to improved source of water such as controlled wells, taps etc.;
- *electricity*: household having access to a power source, no matter if from the electric network or by home generator;
- *safe sewage*: dummy equal to one if sewage disposal is safe (connection to a sewage system, controlled cesspool etc.).

Table A.1. Factor Loadings for the Observed Variable Used to Estimate ABS

Variable	Factor Loadings
health facility	0.782
school	0.781
water source	0.759
safe water	0.676
electricity	0.829
safe sewage	0.875

Agricultural Assets (AA):

- *land*: value of land owned by the household as reported by the respondent;
- *livestock*: measured as tropical livestock units;
- *capital*: value of agricultural machinery and installations owned by the household.

Table A.2. Factor Loadings for the Observed Variable Used to Estimate AA

Variable	Factor Loadings
land	0.675
livestock	0.886
capital	0.852

Non Agricultural Assets (NAA):

- *house value*: the value of the house where the household lives expressed as the house monthly rent;
- *durables*: value of durables owned by the household as reported by the respondent.

Table A.3. Factor Loadings for the Observed Variable Used to Estimate NAA

Variable	Factor Loadings
house value	0.727
durables	0.725

Household Technological Level (TL)

- *production capital*: it is the value of the agricultural and not agricultural capital and installations used (that is owned, hired and shared by the households).

Social Safety Nets (SSN1)

- *institutional transfers*: transfers received by the households from public institutions in form of pensions, social programmes etc.

Social Safety Nets (SSN2)

- *non institutional transfers*: transfers received by the households from other households, NGOs and religious organizations etc.

Adaptive Capacity (AC):

- *employed household members*: number of household members who are income earners, no matter if they are wage worker or self-employed;
- *sectors of employment*: number of sectors where at least one household member is employed;
- *educational attainment*: maximum level of educational attainment among household members and educational attainment of household head;

- *employment ratio*: ratio between the number of household working members and the number of household members aged 15-65;
- *food share*: share of household expenditure made up by food expenditure
- *health insurance*: it is a dummy = 1 if some member of the household have a health insurance

Table A.4. Factor Loadings for the Observed Variable Used to Estimate AC

Variable	Factor Loadings
employed	0.602
sectors of employment	0.744
educational (hh head)	0.348
education (maximum)	0.518
employment ratio	0.663
food share	-0.358
health insurance	0.410

<u>Physical Connectivity (PC)</u>:

- *TV*: dummy equal to 1 if the household owns at least one television;
- *physical access*: dummy equal to 1 if the place where the household lives can be reached through a paved or at least managed road;
- *private transport*: dummy equal to 1 if the household owns at least one motorized private transport means;

Table A.5. Factor Loadings for the Observed Variable Used to Estimate PC

Variable	Factor Loading
tv	0.878
household accessibility	0.692
private transport	0.816

<u>Household Demographics (HD)</u>:

- *dependency ratio*: ratio between the number of household members younger than 15 or older than 65 and total household members;

<u>Economic Connectivity (EC)</u>:

- *market reliance for food*: the share of food expenses in total household expenses;
- *access to credit market*: a dummy equal to 1 if the respondent thinks that, if he needed to borrow a credit financial institutions would not lend him any loan;

- *ownership of financial assets*: a dummy equal to 1 if household owns some form of financial asset.

Table A.6. Factor Loadings for the Observed Variable Used to Estimate EC

Variable	Factor Loadings
market reliance for food	0.671
access to credit	-0.681
financial assets	0.583