Testing for Household Resilience to Food Insecurity: Evidence from Nicaragua

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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 proposed resilience index highlights small landowners and agricultural wage workers as less resilient vis-à-vis other livelihood groups. The analysis shows that the proposed resilience index is a significant determinant of households' food security and this result is robust across several specifications.

Keywords: Resilience, Agriculture, Food Security, Nicaragua

Introduction

The overall objective of this paper is to develop a suitable method to measure household resilience food insecurity and to test it. There are three main empirical research questions we address, namely: How can household resilience to food insecurity be measured? Does household resilience contribute to ensuring household food security? If so, what are the policy implications of it? In doing this, we propose an approach for measuring household resilience, the so-called resilience index, to be used as a predictor of future well-being outcomes, that is in our specific case household food security.

The paper is structured as follows. Next section briefly reviews the empirical approaches to resilience measurement and describes the adopted estimation strategy. The third section introduces the case study – the impact of Mitch hurricane on rural households Nicaragua – and presents the results of the analysis, namely the resilience index estimation and its validation. The last section summarizes the main findings.

Assessing Household Resilience to Food Insecurity

Resilience to Food Insecurity

Following Dercon (2001) we maintain that households and individuals have assets, which are used to generate income in various forms, that in turn provide access to dimensions of well-being, e.g. consumption, nutrition, health, etc., while facing risks throughout this sequence. According to this framework, well-being and any dimension of it, such as being food secure or being non-poor, 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, that is the propensity to fall below a given food consumption threshold, 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, while vulnerability is essentially a forward-looking concept that uses the information at a particular point in time (Chaudhuri *et al*., 2002).

We argue that vulnerability is function of household's risk exposure and 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 so that the household 'functionings' will be ensured).

Estimation Strategy

There are very few studies that have tried to quantitatively assess household's resilience to food insecurity. 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; Demeke and Tefera, 2010) or using an observable variable as a proxy of resilience (Carter *et al*., 2006; Keil *et al*., 2008). We decided to adopt Alinovi *et al*.'s approach because of its flexibility to adapt to very different empirical situations.

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.[2] 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 and dynamic estimators. Unfortunately, until recently it was very difficult to have suitable datasets to implement this estimation strategy in most developing countries, the major limitation being the number of periods over which the cross-sections are observed.

Assessing Resilience to Food Insecurity of Rural Household in Nicaragua

Nicaragua is a suitable case study both in terms of data availability and of the problem to be analyzed, i.e. the impact of the hurricane Mitch on rural households in Nicaragua. Indeed, the available 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.[3] 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.

Resilience Index Estimation

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.[4] This is why we decided to focus on agricultural households only,[5] that

[1] This concept of resilience is essentially the same as 'development resilience' as defined by Barrett and Constas (2012).
[2] As a result, the process of estimating resilience should reckon this and be different according to the different livelihood strategies adopted by each group.
[3] Hurricane Mitch hit Central America between 26th October and 4th November 1998 and is considered as one of the worst ever. It affected 12 per cent Nicaraguan health structures and deeply damaged the infrastructural network in 70 out of 147 municipalities (USAID, 1999). Mitch aftermaths were impressive with losses ranging from 7 per cent to more than 60 per cent of the impacted crops (ECLAC, 1999).
[4] Indeed, estimating household resilience through an econometric model needs to explicitly acknowledge the variety and specificity of people's way to gain their own livelihood to prevent blurring the estimation exercise. If not, the estimated model will identify an average behavior, which is just a statistical artifact not capturing actual behaviors of various livelihood groups.

resulted in a sample size is 1,237 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.

The classification of agricultural households into different livelihood groups has been carried out using cluster analysis, using Euclidean distance and Ward's linkage algorithm to identify livelihood strategy clusters.[6] The cluster analysis identifies four agricultural livelihood strategies (cf. Ciani, 2012 for details), namely agricultural wage workers, *minifundia* owners (farm size below 2 ha), small-medium landowners (average farm size: 16 ha)[7] and large landowners (average farm size: 187 ha).

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.:

$$R_i = f\left(I_i, ABS_i, AA_i, NAA_i, TL_i, SSN_i, AC_i, PC_i, EC_i, HHD_i\right). \qquad (1)$$

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 (1). 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.

Despite our approach is largely based on Alinovi *et al.* (2010), it is worth to point out some revisions we introduced vis-à-vis the original approach. First, this approach does not include stability and food access as right hand side variables in the index estimation model as they are considered as output and not as components of household resilience. Second, the estimation has been refined by the use of polychoric variance and covariance matrixes for the latent resilience dimension carachterised by a large number of binary or categorical variables.

Thus, the resilience index is estimated using a two-stage factor analysis strategy. In the first stage, an index for each component is estimated separately using an iterated principal factor method over a set of observed variables. 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 1 shows the factor loadings of the agricultural resilience index: all signs are positive as expected.

[5] Poverty in Nicaragua is a widespread phenomenon: the poverty headcount ratio, measured according to the national poverty line, decreased only marginally from 50.3 per cent in 1993 to 48.3 per cent 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.

[6] 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).

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

Table 1. 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 landowners are by far the better-off group while *minifundia* owners have the lowest resilience value (Figure 1). Small-medium landowners and wage workers show similar level of resilience although the value of the small-medium size landowners is slightly higher. The western regions (Managua, Northern and Southern Pacific Coast) seems to be much more resilient than the Central and Eastern regions.

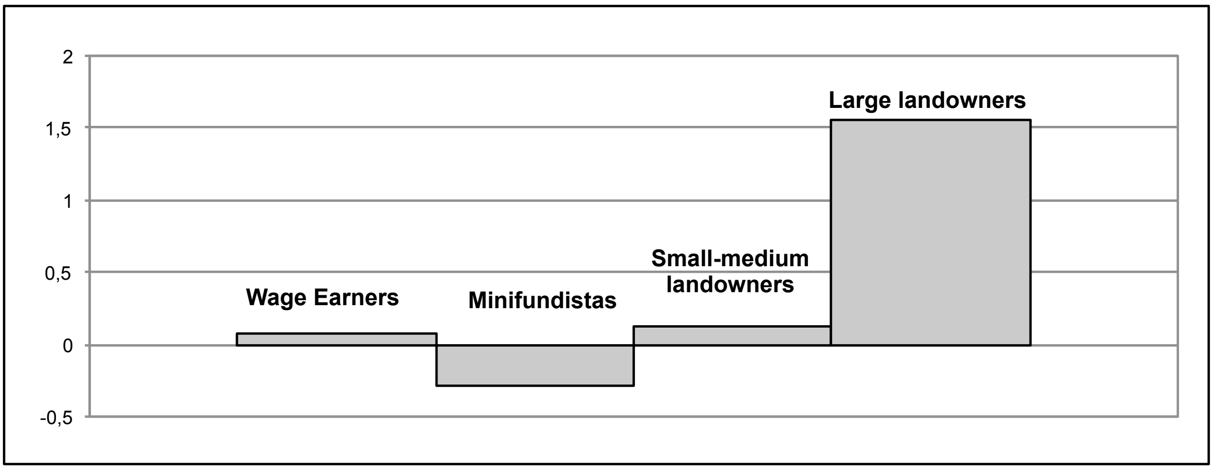

Figure 1. Average resilience level per livelihood groups.

It is interesting to go beyond averages, analysing the contribution of each dimension to resilience per livelihood group. The radar graphs in Figure 2 provide a useful tool to give a snapshot of the situation in each livelihood group.

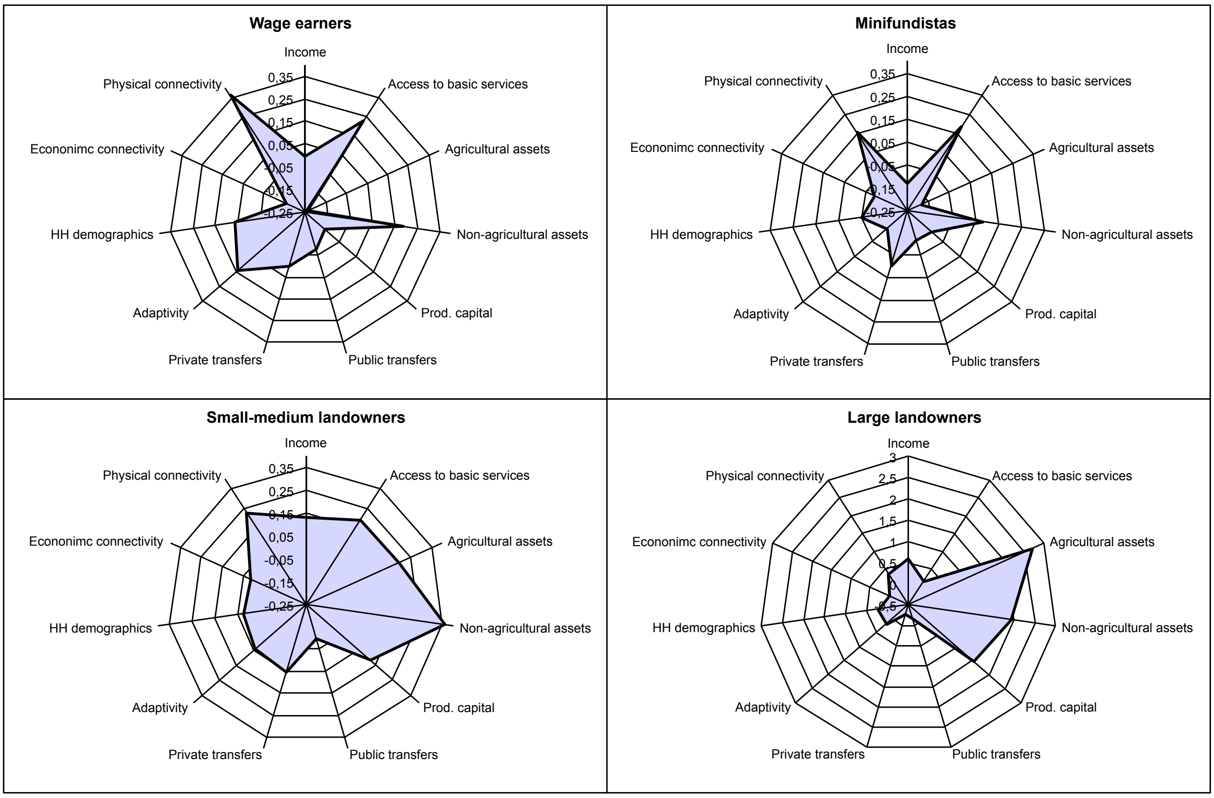

Figure 2. Resilience Determinants per Livelihood Groups.

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[8]. The situation of *minifundia* owners is particularly concerning: they are constrained by their scarce land endowment and are less able to diversify across 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 landowners show very high levels of agricultural and non-agricultural assets as well as production capital.[9]

Resilience Index Validation

The most important research question we address in this paper is whether the construct we are measuring, i.e. resilience, is relevant in predicting future well-being attainments (in our case food security). Nicaraguan EMNV 1998, 1999 and 2001 surveys offer an opportunity to test the validity of the resilience index. In fact, 1,221 agricultural households have been

[8] Indeed, wage-workers are more likely to live in urban areas and more able to diversify across sectors.
[9] Notice that the scale of the large landowners graph is different from that of other graphs. As a result the former cannot be at first glance compared to the other three graphs.

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 2 reports a summary of food poverty dynamics between 1998 and 2001 in the selected sample[10]. 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 food non-poor: about 40.7% of 1998 food poor experienced a transition out of poverty between 1998 and 2001; vice versa only 25.9% of 1998 food non-poor became food poor in 2001.

Table 2. Food Poverty Dynamics in Nicaragua, 1998 – 2001.

		2001		
		Food Poor	**Food Non-Poor**	**Total**
1998	**Food Poor**	296 (24.24%)	203 (16.63%)	499 (40.87%)
1998	**Food Non-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:

$$\Delta FCpc_{(h,t|t+1)} = \alpha R_{h,t} + FCpc_{h,t} + \sum_{i=1}^{k} \gamma_i LIV_{h,t} + \delta \sum_{i=1}^{k} \xi_i S(i)_{(h,t|t+1)} + \mu X_h + \varphi Z_{h,t} + \varepsilon_{h,t} \qquad (2)$$

where the dependent variable, $\Delta FCpc_{(h,t|t+1)}$, is the difference between log food expenditure in 1998 and 2001, i.e. the rate of growth of food expenditure in the period taken into consideration,[11] $R_{h,t}$ 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

[10] 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).

[11] The most appropriate outcome variable would be caloric intake per adult equivalent. 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 tail) 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).

livelihood strategy adopted by the household at time t, S is a vector of shocks occurred between t and $t + 1$, and $\varepsilon_{h,t}$ is a stochastic error term.

Some descriptive statistics of the variables included in the model are reported in Table 3.

Table 3. 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 landowners	binary	0.297	0.457
Wage earners	binary	0.393	0.489
Minifundia owners	binary	0.275	0.447
Small-middle size landowners	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

All the variables but the change in food expenditure and the value of the resilience index are binary variables[12] while the dependent variable is continuous. In such a situation the presence of heteroskedasticity is very likely (Grizzle *et al.*, 1969). 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 to use a weighted least square (WLS) or a variance weighted least square (VWLS) strategy to deal with heteroskedasticity.[13] The estimates of the best models are reported in Table 4.

[12] All dummies should read as 1 when the condition is met, 0 otherwise. The reference variables in each category are "Atlántico" for the region of residence, "Large landowners" for the livelihood group and "Belonging to the 4th quartile" in the distribution of the resilience index for resilience.

[13] Heteroskedasticity was tested 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.

Table 4. 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 landowners	-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 10, 5 and 1 per cent respectively.

Food expenditure growth is slower for households showing a higher initial level of expenditure. Households exposed to natural and anthropic shocks present a slower growth of food expenditure (though these variables are significant only in the VWLS model). As expected, household exposed to hurricane Mitch presents a lower food expenditure growth rate. Resilience is a very robust predictor of food expenditure rate of growth in both models: 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.[14]

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

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

exposure and the first quartile of food expenditure is positive and significant suggesting that households characterized by lower 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 not significant. As expected, large landowners have a systematically higher food expenditure growth rate, just as households headed by a male (though this coefficient is barely significant in the WLS specification).

The same dataset can be also used to explore the relationship between resilience and vulnerability. 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 5.

Table 5. 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 landowners	0.146	0.124	
Resilience Quartile			
Resilience: 3rd quart.	0.146	0.049	***
Resilience: 2nd quart.	0.191	0.049	***
Resilience: 1st quart.	0.302	0.050	***
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 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 percentage points. 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 percentage points and -13.2 percentage points. The model confirms the difficulties of *minifundia* owners who have an higher probability of being poor 2001 (+24.5 percentage points). 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 quite surprisingly more likely 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 6).

Table 6. 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 landowners	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 10, 5 and 1 per cent respectively.

Living in the Northern Highlands region increase the transition probability by 14.4 percentage points while to live in Rio San Juan and in North Pacific Coast has an opposite effect (-11.3 and -8.9 percentage points respectively). Living 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 7 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. 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.[15] All livelihood groups other than large landowners present a lower transition probability if compared to large landowners, although small-medium size landowners show a slightly higher coefficient than wage earners and *minifundistas*. In this model too, household with a white household head shows a worse performance, with a lower probability of transition out from poverty (-21.2 percentage points).

Table 7. 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 landowners	-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 10, 5 and 1 per cent respectively.

Conclusions

The basic problem concerning resilience measurement is that resilience is not directly observable. We used a revised version of the multivariate analysis approach originally proposed by Alinovi *et al*. (2008 and 2010) which models resilience as a latent variable. We developed also a dynamic specification of household food security that made possible to validate the measurement approach.

Our results prove that the resilience index is consistently a significant and 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

[15] 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.

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 food non-poor to being food poor between t and $t + 1$.

The reliability of our results is supported by the resilience profiling emerging from our analysis, 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.

The major limitations of the proposed approach are in terms of data needs and comparability of results. In fact, the proposed quantitative assessment is very demanding in terms of data: it 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 study 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. In fact, 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.

Finally, 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 analysis to a more aggregated level (e.g. community).

References

Alinovi, L., D'Errico, M., Mane, E., and Romano, D. (2010). Livelihoods Strategies and Household Resilience to Food Insecurity: An Empirical Analysis to Kenya. Background paper to the European Report on Development 2010. Florence: European University Institute.

Alinovi, L., Mane, E., and Romano, D. (2008). Towards the Measurement of Household Resilience to Food Insecurity: Applying a Model to Palestinian Household Data. In Sibrian R. (ed.), *Deriving Food Security Information From National Household Budget Surveys. Experiences, Achievement, Challenges*. Rome: Food and Agriculture Organisation (FAO), 137-52.

Barrett, C.B., and Constas, M.A. (2012). Resilience to avoid and Escape Chronic Poverty: Theoretical Foundations and Measurement Principles. Cornell University. Mimeo. November 2012.

Breusch T.S. and Pagan A.R. (1979). A Simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica* 47(5): 1287-1294

Carter M.R., Little P.D., Mogues T., and Negatu W. (2006). Shocks, Sensitivity and Resilience: Tracking the Economic Impacts of Environmental Disaster on Assets in Ethiopia and Honduras. DSGD Discussion Paper 32. Washington D.C.: International Food Policy Research Institute (IFPRI).

Chaudhuri, S., Jalan, J., and Suryahadi, A. (2002). Assessing Household Vulnerability to Poverty from Cross-Sectional Data: a Methodology and Estimates from Indonesia. Discussion Paper Series 52. New York: Columbia University.

Ciani, F. (2012). A Resilience-Based Approach to Food Insecurity: The Impact of Mitch Hurricane on Rural Households in Nicaragua. Dissertation Submitted in Partial Fulfillment of the PhD Program in Development Economics. Department of Economics and Management, University of Florence.

Davis, B. and Stampini, M. (2002). Pathways towards Prosperity in Nicaragua: an Analysis of Panel Households in the 1998 and 2001 LSMS Surveys. Background Paper Prepared for the 2002 Nicaragua Poverty Update. Washington D.C.: The World Bank.

Demeke, M., and Tefera N., 2010. Household Resilience to Food Insecurity in Ethiopia: Panel Data Evidence. Rome: Food and Agriculture Organisation (FAO-ESA). Mimeo.

Dercon, S. (2001). Assessing Vulnerability to Poverty. Oxford: Department of Economics, University of Oxford.

ECLAC. (1999). Nicaragua: Assessment of the Damages Caused by Hurricane Mitch. Santiago de Chile: Economic Commission of Latin America and the Carribean (ECLAC).

Grizzle, J.E., Starmer, C.F., and Koch, G.G. (1969). Analysis of Categorical Data by Linear Models. *Biometrics* 25(3): 489–504.

Heckman, J.J., LaLonde, R., and Smith, J. (1999). The Economics and Econometrics of Active Labour Market Programs. In Ashenfelter, O. and Card, D. (eds.), *Handbook of Labour Economics* , Amsterdam: North-Holland, 1865–2097.

IMF. (2010). Nicaragua: Poverty Reduction Strategy Paper. Washington D.C.: International Monetary Fund (IMF).

Keil, A., Zeller, M., Wida, A., Sanim, B. and Birner, R. (2008). What Determines Farmers' Resilience towards ENSO Related Drought? An Empirical Assessment in Central Sulawesi, Indonesia. *Climate Change* 86: 291-307.

USAID. (1999). Hurricane Mitch Reconstruction: USAID/Nicaragua Special Objective. Washington D.C.: USAID.

World Bank. (2003). Nicaragua Poverty Assessment. Raising Welfare and Reducing Vulnerability. Report 26128-NI. Washington D.C.: World Bank.