WPS7170

Policy Research Working Paper 7170

Can We Measure Resilience?

A Proposed Method and Evidence from Countries in the Sahel

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WORLD BANK GROUP
Poverty Global Practice Group
January 2015

Abstract

Although resilience has become a popular concept in studies of poverty and vulnerability, it has been difficult to obtain a credible measure of resilience. This difficulty is because the data required to measure resilience, which involves observing household outcomes over time after every exposure to a shock, are usually unavailable in many contexts. This paper proposes a new method for measuring household resilience using readily available cross section data. Intuitively, a household is considered resilient if there is very little difference between the pre- and post-shock welfare. By obtaining counterfactual welfare for households before and after a shock, households are classified as chronically poor, non-resilient, and resilient. This method is applied to four countries in the Sahel. It is found that Niger, Burkina Faso, and Northern Nigeria have high percentages of chronically poor: respectively, 48, 34, and 27 percent. In Senegal, only 4 percent of the population is chronically poor. The middle group, the non-resilient, accounts for about 70 percent of the households in Senegal, while in the other countries it ranges between 34 and 38 percent. Resilient households account for about 33 percent in all countries except Niger, where the share is around 18 percent.

This paper is a product of the Poverty Global Practice Group. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at vmolini@worldbank.org.

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JEL classification: C14; D91; D61; I32

Keywords: Resilience, consumption, malnutrition, counterfactual distributions

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1 Introduction

Africa sits at the cusp of an enormous opportunity to reduce poverty. Economic growth appears to have taken hold, the private sector is expanding, ambitious investment plans are being implemented, and citizens from East to West, and North to South are demanding, and in many cases getting, reforms towards good governance. But the gains from these opportunities are tempered by huge vulnerabilities - from macro shocks, conflict and state fragility, weak institutions, and climate change. As the recent experience of the 2010 fuel and food crisis shows, a single large shock is enough to strain the resilience of plenty of households at once. When such shocks occur in succession, the consequence is often a breakdown in resilience and large welfare losses. The poorest households are confronted often with a multiplicity of shocks: droughts or floods reduce grain supplies, prices spike, and health shocks strike. To worsen the situation, public institutions in the region are generally not adequately equipped to compensate through safety nets or buffer food stocks; at the same time, traditional responses that are effective against small-scale shocks are gradually losing momentum.

The erosion of traditional safety nets based on self- and mutual insurance and the inadequate responses of state interventions is undermining the resilience of the population in Sub-Saharan Africa. Some have developed diversification strategies, mostly through rural-urban linkages that provide income from off-farm activities and remittances that are less risky than farm income or have an uncorrelated risk. When negatively correlated with farm income, these income sources can act most effectively as a safety net (Yang and Choi, 2007). However, other households, unable to engage in such activities have continued to resort to low risk management. But even those with the least risky profiles are often exposed to covariant income shocks that may bring them to extreme poverty with associated problems of destitution and inability to recover - that is, they may be caught in poverty traps.

The Sahel region illustrates the problem of (poor) resilience in a particularly stark way. These countries rely on at most two commodities – cotton or peanuts and gold, oil or uranium – that are highly sensitive to world demand shocks for export earnings. Attempts to diversify their economies have been unsuccessful to date. Also, Mali, Burkina Faso and Niger are particularly disadvantaged by geography and by their own instability and that of neighboring countries. As an illustration, between 2007 and 2012, these countries have had to deal with global food and financial crisis, droughts and economic disruptions and social tensions from conflicts in Côte d'Ivoire, civil war in Libya and civil war and a coupe d'état in Mali.

Whereas resilience -or lack thereof- is a widely used concept, it has been a lot harder obtaining a credible measure of it. This is in part because the data that are needed to measure resilience are typically the same or in many ways similar to those needed to understand vulnerability and are rare – that is, panel data of individuals, communities or countries, knowledge of types of shocks that hit them, and welfare outcomes after every exposure. In the absence of these ideal data sets, at least for the Sahel

region, this paper proposes a simple measure of resilience that makes use of currently available information.

The quantitative measure we provide builds on the intuitive understanding of resilience. When a household (or individual) is hit by a shock, the household is resilient if there is very little difference between its pre-shock welfare and the post-shock welfare; there is indeed little deviation from the household's long-term (permanent) welfare trajectory. If we use cross sectional data sets, we do not observe the same individual and we do not have the opportunity to measure the post-shock outcome.

To overcome this limitation, we simulate the counterfactual outcome, using present available information. The counterfactual outcome is the hypothetical welfare outcome that a household would obtain if faced with a different state of the world. For this, we rely on the vast literature using counterfactual distributions (Fortin et al. 2008; Graham et al, 2008) and survey to survey imputation (Elbers et al., 2003). The methodology is pretty straightforward. We first split the sample into households (or individuals) which experienced shocks, which we refer to as the subpopulation of the treated – and those which did not, often referred to as the control subpopulation. Next, we estimate separate welfare outcomes for those who received a shock and those who do not. We use these parameters to obtain the counterfactual distributions for each group. The comparison of the permanent welfare and counterfactual distribution outcome for each individual gives an indication of who is likely to be resilient and who is not.

We provide estimates of rates of resilience for two alternative measures of welfare: consumption and a measure of child nutritional deficiency – weight for age. We find that using consumption as the welfare measure, about 35% of the households in the West African Sahel would be considered resilient. However, when we use underweight as the welfare measure, we find that on average, only about 25% of the children in the 1-3 years age group in the Sahel, are resilient. However, this average hides large variations in the region. Those who can be considered resilient to underweight range from about 35% in Senegal to less than 20% in Burkina Faso.

The paper is divided into seven sections. Section 2 is a literature review. Section 3 covers the theoretical model while section 4 is the empirical strategy. Section 5 discusses the data used and section 6 presents results. Section 7 concludes.

2 How do we define resilience? A Literature Review

This section provides a quick overview of the growing literature on resilience. The literature falls into three categories. One is mostly conceptual and concerned with how to define and think about resilience. There is another that does not invoke the concept of resilience but through its focus on coping strategies implicitly offers evidence of resilience. And finally, another category provides empirical estimates of resilience. We summarize each in turn.

Defining resilience: Resilience has been defined as "…the ability of countries, communities and households to manage change, by maintaining or transforming living standards in the face of shocks or stresses - such as earthquakes, drought or violent conflict - without compromising their long-term prospects" (DFID, 2011; Walker et al. 2004; World Bank, 2013). This definition conceives of resilience not only as the ability of economic agents to return to their previous state, but also as an inclination of these agents to strengthen their adaptive capacity to the post-shock situation.

In recent years, resilience has become more and more attractive as a goal of economic development, because it implies the capacity of economic agents to cope successfully with a wide array of shocks (e.g. environmental, economic, social, political, demographic, religious). Accordingly, the level of vulnerability and the capacity to cope with shocks depend on the nature of the disturbance and the availability of additional resources, such as alternative income, credit capacity, and public assistance. Resilient individuals, communities and households are therefore, seen to be able to meet their food security needs, have access to adequate nutrition, protect their environment, have income and health security, educate their children, and participate in the decisions that affect their lives (Frankenberger et al., 2012). During the last decade, several studies have linked environmental sustainability to concepts of resilience (Morduch, 1993; Mercer, 2010; Bahadur et al., 2010).

Coping and lack of resilience: Although not explicitly stated as resilience, other studies that have analyzed a variety of coping strategies used by households in different countries (e.g. decrease in fertility rates, increase in private borrowing, relying on local support networks, etc.), in an attempt to protect their welfare do come across as measures of lack of resilience. Skoufias (2003) reviewed 12 such studies and also analyzed the interaction between household coping strategies and the impact of crises and natural disasters on different dimensions of well-being. In general, these studies conclude that while the informal efforts put in place by households and/or communities to mitigate and cope with risk were perhaps unavoidable and worked for a few cases, they remained ineffective. Therefore, households were forced to rely on self-insurance strategies that are particularly costly in terms of current as well as future welfare. Such ineffective strategies have been documented across the developing world. Examples include reduction in expenditures, asset sales, and increased private borrowing and debt by Bangladesh households coping with the 1998 floods (Del Ninno et al. (2003)), in Ethiopia (Carter et al., 2006; World Bank, 2005), Southern Zambia (Umetsu, 2010) and Indonesia (Keil et al., 2008). Using about 9,000 farm surveys across Africa, Seo (2010) estimates net revenues associated with different types of farm systems and shows that farmers who moved from a specialized crop farm to an integrated system that mixes crops and livestock are more resilient against climatic shocks.

Measuring resilience: Although a broad literature on resilience exists, there is no consensus yet on how to measure it among the limited set of examples that have attempted to go in that direction The latest contribution is a group of papers that apply a latent variable approach. They propose the idea that resilience is multifaceted and, therefore, not observable per se but can be related to a number of observable context-specific dimensions. These dimensions can be reduced to a single variable, by

applying data reducing techniques, such as Principal Component Analysis (PCA) and Factor Analysis (FA).

One such paper considers resilience as a latent variable defined according to four main opportunities (i.e. income and food access; assets; access to public services; and social safety nets) and two additional dimensions (i.e. stability and adaptive capacity). The paper applies a factor analysis to these variables to obtain a resilience index which, together with other household covariates is entered into a regression of food security in the West Bank and Gaza (Alinovi et al. 2009). Regression results showed that resilience is one of the most important indicators in measuring vulnerability to food insecurity.

Ciani and Romano (2013) also developed a methodology to quantitatively assess resilience to food insecurity among rural households hit by Hurricane Mitch in 1999 in Nicaragua. The authors made use of a two-stage factor analysis on a nationally representative longitudinal data set of around 3,000 households, of which 540 were re-interviewed after the hurricane occurred. The resilience index resulting from the analysis seems to be a key element describing future households' well-being attainments. The econometric analysis carried out by the authors on different outcome variables such as the growth rate of food expenditure and the transition both into and out of food poverty, and including the resilience index among the explanatory variables, shows a positive relationship between households' resilience at time t and the level of food security at $t+1$ and the probability of moving out of poverty between t and $t+1$. At the same time, lower levels of resilience at time t are shown to be related to higher probabilities of being food deficient at $t+1$ and of moving from being food sufficient to being food poor between t and $t+1$.

Demeke and Tefera (2011) use data from the Ethiopia Rural Household Survey to estimate household resilience to food insecurity. The authors derived a resilience index through the Principal Component Analysis on a set of variables such as food access, liquid assets, education, and social network. Determinants of resilience were then explored using a dynamic panel model. Results suggested that there is a significant state-dependence of the dynamics of resilience with food insecurity (i.e. current resilience status is affected by its past level). Furthermore, the probability of being resilient is also shown to depend on a number of physical, human, financial and social characteristics, as well as access to basic services, information, agricultural inputs, markets and income diversification. Access to productive assets seemed to play a crucial role in this context and to be positively associated with households' resilience, whereas, access to credit in the form of short-term loans from informal sources showed a negative impact on the probability of being resilient, and traditional saving and credit arrangements both had a positive and significant effect.

In the next section we will provide a theoretical framework for understanding resilience and follow that with an empirical strategy for measuring it explicitly.

3 Theoretical framework

Studies of village economies in developing countries have shown that random variation in incomes of households need not result in consumption variation, because in the presence of risk, informal insurance markets that are mediated through community and family relationships may be able to overcome the absence of formal insurance markets (Udry, 1994; Townsend, 1994). According to the literature, these informal risk pooling arrangements can arise for a variety of reasons. They could come about because of communal solidarity that emerges from shared norms and moral values (Platteau, 1991) or from trading by risk-averse individuals trying to reduce their risk exposure (Arrow, 1991). In the latter case, there is usually even no need for a third party enforcer. Rather, repeated interactions are considered sufficient to convince rational actors that cooperation is less costly than non-cooperation.

Our conceptual motivation for resilience can be best understood within this rich and diverse literature that attempts to model and test consumption smoothing by households in a risky environment in village economies. The starting point is a life-cycle consumption smoothing model, where the household tries to deploy multiple resources to maintain its permanent income trajectory. Therefore, consider a risk-averse household, h, who maximizes an inter-temporal expected utility defined over a consumption good, c, and a planning horizon comprising T periods. The household has access to a risk-free asset, A, which earns interest, r. It also earns a risky income, y, in each period. The household's maximization problem can be stated as,

$$Max\ U(c_{ht}) + \beta^t E\lfloor \sum_{t=1}^{T} U(c_{ht+1}) \rfloor \qquad (1)$$

Subject to the budget constraint,

$$A_{ht+1} = (1 + r_t)A_{ht} + y_{ht} - c_{ht} \qquad (2)$$

where β is the time discount rate.

The usual solution to this programming problem is that households solve the maximization problem so as to equate the marginal utility of current consumption to the discounted expected marginal utility of future consumption. That is,

$$U'(c_{ht}) = \beta\ (1 + r)EU'(c_{ht+1}) \qquad (3)$$

This framework allows us to test whether a household, in general, can maintain its permanent income under conditions where risk is prevalent. It is the framework deployed most often by a wealth

of studies that examine how and whether households living in village economies have access to credit that allows them to ride out the risks they encounter in that context (see Morduch, 1995; Alderman and Paxson, 1992 for thorough reviews). As an illustration, consider a household that has to self-insure. In such a case, the household would save a share of the portfolio that the household decides to keep in the form of currency or other transferrable form of wealth, plus the income from risky production in order to minimize the difference between its permanent income and state-of-the-world contingent income. Household resilience can, thus, be seen as an inter-temporal risk minimization problem subject to a resource constraint. However, in many contexts individual households would not be able to save enough to self-insure. Therefore, in our empirical models that follows we take it as a given that households rely on multiple sources of income – own resources, credit, mutual insurance, and so on – to protect themselves from large deviations from potential welfare.

Empirical models usually require two additional assumptions in order to implement the test. First, the models work well when we have multiple observations for each household – that is panel data. Second, assumptions are made regarding the structure of the utility function. The two common assumptions are to assume either constant absolute risk aversion (CARA) or constant relative risk aversion (CRRA).

Two variants of the test have been used in the empirical work. One tests for risk sharing across villages, regions or even countries. The full insurance model assumes that the village resources will be distributed across households until the (weighted) marginal utilities of consumption are equalized across households. Therefore, consumption of a household in any given period will be a function of the average consumption in the village plus some deviation that accounts for that household's preferences and circumstances (e.g. its household size, demographic composition, health status of its members, etc.).

The second tests for whether a household's consumption trajectory is sensitive to transitory shocks to income. Consider the model,

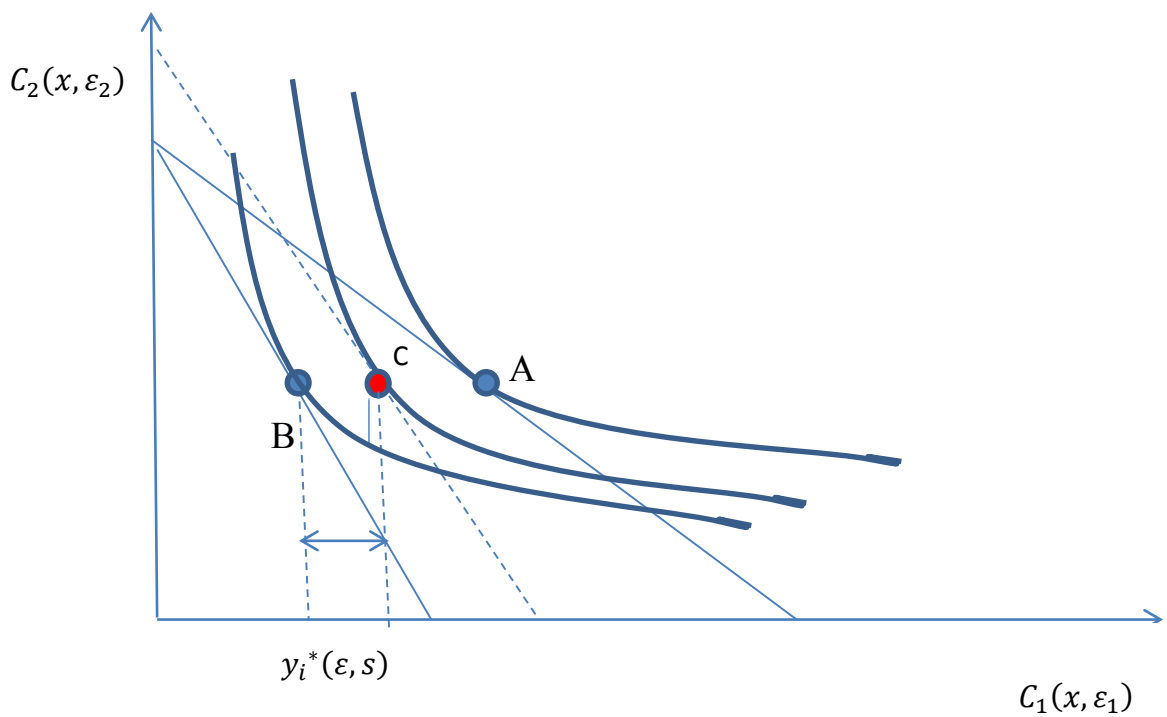
$$c_{it} = \alpha + \gamma_1 Y_{it}^{p} + \gamma_2 Y_{it}^{R} + \gamma_3 Y_{it}^{U} + \delta X_{it} + \epsilon_{it} \qquad (4)$$

where Y, denotes household incomes and superscripts p, R, U denote permanent, transitory and residual incomes, X, and ϵ are other household covariates and unobservables, respectively. The permanent income test posits that the transitory incomes will be smoothed away and the only part of income that affects the trajectory of consumption is the permanent income part.

So how do these tests relate to a definition of resilience? Note that both tests directly or indirectly suggest that a household can recover relatively quickly from a shock if it can rely on communal resources (village support, family networks, credit and savings associations, etc.) – and we may add even public resources such as safety nets – or has substantial resources of its own (savings, stable job or business, etc.). By contrast a household that does not have such resources will not be able

to finance its optimal consumption plans. Therefore, in the event of a shock, it will not be able to recover quickly from a large deviation from its optimal consumption trajectory. In other words, it will not be resilient. Figure 1 provides a simple illustration of the problem faced by the household in a two period setting. $C_1(x, \varepsilon_{1)}$ and $C_2(x, \varepsilon_2)$ are welfare in periods 1 and 2, for a household with characteristics x, in two states of the world (ε_1 , ε_2). The price of welfare in period 1 is normalized to 1. The price of the welfare good in period 2 is 1/1+r; which is also the price of welfare in period 2 relative to welfare in period 1: Gross interest rate 1 + r is the relative price of welfare goods today compared to welfare goods tomorrow. Before the shock, the household is at point A, which we assume to be the permanent welfare level. After the shock occurs the price of welfare in period 1 increases dramatically, relative to welfare in period 2. The new equilibrium moves to point B with new prices but also with lower welfare level. A resilient household would manage to mobilize an amount of resources comprising a share of assets, s, and income from a variety of sources equivalent to $y^*(\varepsilon, s)$ that brings it back to an equilibrium point C. In other words, a resilient household is one that is successful at minimizing the gap between A and C.

Figure 1: Resilience in a 'two states of the world' setting



As noted above, these potential tests of resilience require data that have multiple observations per household. Collection of comparable surveys before and after a shock can provide a lot of information on households' resilience capacity. However, panel data are rare in developing countries, and are nonexistent in the study countries – with the exception of two rounds of panel in Nigeria. Therefore, there is a need to develop such a measure using more readily available cross section surveys. We now explain our empirical strategy for obtaining a measure of resilience in the West African Sahel.

4 Empirical Model

In the absence of panel data, the major hurdle we face, when we use the cross section data to estimate resilience, is a missing data problem. Our interest is to estimate whether a household (or individual) exposed to a shock is resilient or not. Our empirical strategy makes use of easily available cross section data. However with cross sections, we only observe one observation of the outcome variable per household when in fact we need at least two (and in an ideal case many more), one before and another after the shock. Our proposal is to rely on the insights of literature on program evaluation. A central problem studied in that literature is how to recover the missing data for the outcome of interest (see a recent review by Imbens and Wooldridge, 2008). To see this, suppose we observe h=1,...,N households. These households face a positive probability of exposure to a shock. And for each we assume there are two potential outcomes, $C_h(0)$ and $C_h(1)$. Suppose that the first outcome is the welfare (consumption, income, nutrition, etc.) that would be observed if the household did not experience a shock, and the second outcome denotes the observed welfare after the household experiences a shock. At any given point in time, a household is either exposed to a shock or not, but not both at the same time. If a household is not exposed, then we observe the first outcome and the second outcome becomes the ex-post counterfactual outcome. If a household is exposed to a shock we observe the second outcome, and the first outcome becomes the ex-post counterfactual (Imbens and Wooldridge, 2008; Fortin, Lemieux and Firpo, 2010).

Given this setup, we have two challenges to estimate resilience. One is that we have to obtain an estimate of the counterfactual which in both subpopulations is not observed. Second, we have to determine a rule for considering a household resilient or not. To obtain the counterfactual we use the Oaxaca-Blinder framework, we subdivide households into two different groups based on their exposure to shocks. To stay with the usual language in the literature, denote the two subpopulations of treated and non-treated as, s, and ns, respectively. We define these subpopulations as

$$s = \{h_i: R_{it-1} < \bar{R}_i\} \quad and \quad ns = \{h_i: R_{it-1} \geq \bar{R}_i\} \qquad (5)$$

That is, a household belongs to the treated subpopulation if last period (defined as the year before the start of the survey) shock (e.g. rainfall) is below a specific threshold, and it belongs to the

control group if last period shock is greater than the threshold. Then we can express the welfare measure of interest as,

$$C_{hi} = \alpha + \beta^i X_{hi} + v^i \qquad (6)$$

for $i = s, ns$. Obtaining the counterfactual welfare involves estimating the same model separately for each subpopulation, and then applying the resulting parameters to the other subpopulation and adding the bootstrapped residuals[1]. The imputation process is a simplified version of the methodology developed in Elbers et al. (2003). Stifel and Christiaensen (2007) provide theoretical guidance regarding variables to be included in imputation models. Following Stifel and Christiaensen (2007), we included several household durables, household characteristics, location, and interaction (especially with location) variables. For the treated, the ex-post counterfactual – the potential welfare outcome if they did not experience a shock – is the mean welfare using the treated's covariates and the parameters obtained from the model of those not experiencing a shock. That is,

$$C^c_{h,s} = \alpha + \widehat{\beta^{ns}} X_{hs} + \widehat{v^{ns}}_{it} \quad for\ i \in s = \{h_i : R_{it-1} < \bar{R}_i\} \qquad (7)$$

$$C^c_{h,ns} = \alpha + \widehat{\beta^{s}} X_{it} + \widehat{v^{s}}_{it} \quad for\ i \in ns = \{h_i : R_{it-1} \geq \bar{R}_i\} \qquad (8)$$

where the superscript for the outcome variable denotes the estimated counterfactual outcome.

Resilience is then tested by comparing the counterfactual to the permanent welfare value $\bar{C}$ estimated as:

$$C_{it} = a + \beta X_{it} + v_{it} \quad for\ i \in s \cup \text{ns} \qquad (9)$$

We obtain three outcomes

A) $\bar{C}_i$<l, the permanent welfare is below the estimated permanent welfare threshold. The household is **chronically poor/deprived.**

B) $\bar{C}_i \leq C^s_{it}$, $\bar{C}_i \leq C^{ns}_{it}$ the counterfactual value is equal to or higher than the estimated permanent welfare measure, the household is **resilient.**

[1] The procedure follows two stages. First, we estimate a model of log per capita real expenditures in one group. Residuals are decomposed into two independent components: the cluster-specific effect, and a household-specific effect. This structure allows both a location effect – common to all households in the same area – and heteroskedasticity in the household-specific errors. To control for this location effect and heteroskedasticity we draw errors from the distribution of residuals for households in the same zone. We divide the sample into zones that differ across countries; these zones are broad enough that they contain every group (treated and control) in all the zones. The sample used to obtain the counterfactual distribution is also divided using same methodology of the original sample. Residuals are then drawn and imputed to households within each of the zones. We obtain the residuals for each household via the bootstrap: that is, we draw 100 replications so as to obtain a number R of distributions, and then average over the 100 replications to obtain the final counterfactual value of residuals for each household..

C) $\overline{C_\iota} > C_{it}^{s}$, $\overline{C_\iota} > C_{it}^{ns}$ the counterfactual value is below the estimated permanent welfare measure, the household is **non-resilient.**

There are several points to note regarding this empirical setup. First, we set the reference minimum threshold equal to 1 in order to avoid counting as resilient households which are living permanently below the welfare minimum threshold because they are too poor. That is, we want to avoid mistaking households whose permanent and counterfactual welfare rarely differ because they are chronically poor or malnourished (that is, outcome A above). The minimum threshold can be read as the poverty line when using consumption as the welfare measure or a value that is -2 standard deviations when the welfare measure is weight for age. Second, although we are using the Oaxaca-Blinder framework to obtain the counterfactual welfare, we are not decomposing changes between the treated and control. Instead, we use the Oaxaca setup to obtain the counterfactual welfare only. We then compare an estimated permanent welfare and the counterfactual income for the same household or individual.

Nonetheless, a question that will arise is whether the treated and the control can be considered as interchangeable – that is, can they serve as suitable samples to obtain counterfactuals for the other or does one need to reweight the samples using any suitable reweighting estimator. It is worth noting, and this serves as the third remark, that the Oaxaca-Blinder estimator is in fact in the same class of reweighting estimators of the conditional odds of being treated. Moreover, it enjoys the status of a doubly robust estimator of counterfactuals which means that the estimation is consistent if either the specification for the propensity score or the outcome variable is correct (Kline, 2011). This means that results from applying the Oaxaca-Blinder framework are enough to provide us with appropriate counterfactuals. Finally, separate from the issue of interchangeability is whether the distribution of shocks is random. If shocks are not random, then the treated and control are essentially different and the estimation strategy for the counterfactuals would have to be different too and considerably harder. One argument often advanced regarding the non-randomness of shocks is the idea that in risky environments households would usually take actions ex-ante to minimize the downside losses of shocks. This is of course true, but it does not follow that shocks are not random. Our view is that conditional on whatever ex-ante action households take, the arrival of shocks is randomly distributed over short periods of time – say one rainy season ahead – over space such that there is little or no likelihood that households would have sufficient information and time to take actions that would lead them to avoid the shock (e.g., through movement to another location).

In the empirical models estimated below, we use different welfare indicators: consumption, weight for age (under nutrition) and weight for height (wasting). Stunting, or the height for age measure that is usually used as a sign of long term nutritional deficiency was judged not suitable for this analysis. Deviations from the norm tend to be permanent; it is often very difficult for individuals to recover from early life damage. On the other hand, underweight can be reversed faster and, if not caused by chronic unfavorable conditions, also wasting can be reversed over a short period.

For consumption models in Burkina Faso, Niger and Senegal, where geocodes are not available in the surveys, we define the treated as those experiencing a level of rainfall (R_{it-1}) during the previous growing season (June to November of the previous year) below the long run mean $\bar{R}_i$. The control group is the one experiencing the long run mean or higher level of rainfall. For the Northern Nigeria consumption model (North East, North West and North Central zones) and for the weight for age Sahel model (including Northern Nigeria, Northern Ghana, Mali, Burkina Faso and Senegal), R_{it-1} defines the greenness index (NDVI), as explained in the data section below.

5 Data and Descriptive Statistics

The Sahel region is facing continuing food and nutrition crises with many vulnerable households struggling to recover. This situation is exacerbated by different environmental, economic, social, political, and religious events that may hit governments, communities and households, undermining all the efforts to fight hunger and chronic poverty. In order to identify the level of households' resilience this study relies on four types of data, namely, i) consumption data from household surveys conducted by local National Statistical Offices; ii) the Demographic and Health Surveys (DHS) designed, implemented and collected by the United States Agency for International Development (USAID); iii) the monthly level of precipitation from 1998 to 2012, produced by NASA through the Tropical Rainfall Measuring Mission (TRMM) project; and finally iv) the Normalized Difference Vegetation Index (NDVI) also collected by a satellite operated by NASA.

5.1 Consumption Data

For Burkina Faso, information on households' living conditions is drawn from the Survey-based Harmonized Indicators Program (SHIP) including a set of harmonized variables on household consumption, access to infrastructure i.e. water, electricity, education and health care, employment status, education and health. These variables have been extracted from the Enquête Burkinabé sur les Conditions de Vie des Ménages (EBCVM) conducted by the National Statistical Office in 2003 and 2009/2010, and covering the 13 regions of the country. The survey undertaken in 2003 includes a sample of 8,510 households, whereas the one carried out in 2009/2010 is made up of 8,470 households. Data are deflated using a 2005 deflator. As welfare threshold we use the national poverty line constructed in 2010.

In Nigeria we selected only three Northern regions since their agro-climatic conditions tend to be similar to those of other Sahel countries. We used the General Household Survey (GHS) panel consisting of 5,000 households. The panel covers the periods 2010/2011 (Wave 1) and 2012/2013 (Wave 2). It is representative at the national and zonal (geo-political) levels. Besides the questions asked in a normal GHS survey, it contains data on agricultural activities and other household income activities. Consumption data are collected using a 7-day recall period. In every panel wave, households

are interviewed two times: once in the "post-planting" period, from August to November, and once in the "post-harvesting" period, from February to April. Data are deflated using 2010 as the base year. The poverty line is the national poverty line in 2010 used for calculating the most recent (unofficial) poverty figures (NER, 2014).

In 2001, the Senegalese national statistics office (ANSD) implemented the second Enquête Sénégalaise Auprès des Ménages (ESAM2), and in 2005, the first Enquête de Suivi de la Pauvreté au Sénégal (ESPS1). ESAM2 consists of about 4,562 households while in ESPS1 10,780 households were interviewed. These surveys were conducted at different times of the year but for the purpose of our analysis they are comparable. One has to just bear in mind that the 2005-06 survey, conducted just after the harvest, may have underestimated the level of poverty. In Niger, we used the 2007 round of Enquête Nationale de sur le Budget et la Consommation des Ménages au Niger (ENBC). Due to security concerns, the rural part of Agadez region was not covered.

5.2 Demographic and Health Surveys

The data on child health come from various rounds of the Demographic and Health Surveys (DHS) that are financed by the United States Agency for International Development (USAID) and implemented by ICF[2]. The DHS collects information on different topics such as fertility, family planning, reproductive health, child health, and HIV/AIDS, reflecting the situation of the country analyzed. The surveys are nationally representative. Child height and weight are converted into standardized Z-scores using WHO methodology. For each child, the Z-score expresses anthropometric values in terms of standard deviations below or above the median of an international reference group.

Table 1 presents some summary statistics on the prevalence of malnutrition in the region over the last decade. We dropped Mali 2001 because we could not link the household data to rainfall in the year prior to the survey. In contrast, all other countries have two rounds. As in the case of consumption, we restricted our sample to Northern Nigeria and Northern Ghana. With the notable exception of Senegal and Northern Ghana in 2008, about one-third of sampled children are underweight (column 3) and more than 10% are severely underweight (column 4). Percentages are similar for stunting (column 7 and 8) but lower for wasting. Burkina Faso and Northern Nigeria show particularly high rates over all the measures. In the analysis we used -2 standard deviations as the minimum threshold for permanent welfare.

5.3 Rainfall

[2] ICF recently acquired MACRO internationational which used to be the main implementator of DHS surveys on behalf of USAID.

NASA's Tropical Rainfall Measuring Mission (TRMM) provides a detailed and comprehensive data set on the four dimensional distributions of rainfall and latent heating over vastly under sampled oceanic and tropical continental regimes. This study links the DHS cluster-level and GHS Enumeration Areas (EA) GPS-coordinates and provinces, with data from TRMM satellites that measure rainfall at a 0.25x0.25 latitude/longitude grid. The data are available every month from January 1998 to December 2012 and the unit of observation used here is average rainfall (in mm/hour).

For each DHS cluster/ GHS (EA), monthly rainfall is estimated using the four nearest data points available in the TRMM data. The estimated rainfall in the cluster is calculated as the weighted average of the measured rainfalls in these four points, which represent the four corners of the world of the gridded cell to which the cluster belongs. The weights of the equation are the inverse distances between the two points, so that the nearer they are to the cluster/ EA the larger the weight assigned to the data points. For household survey data, we aggregate the average of the rainfall observations falling within the geographical limits of the province of a country. Similarly, in the case of households' living conditions data, the rainfall value for households located in each province is simply comprised of the average of the rainfall measured in the TRMM points located in a given province.

Figure 2 shows the amount of rainfall precipitation during the growing period (between June and September/October) over the last 10 years. This period accounts for about 80% to 90% of the total precipitation over the year and it is crucial for crop growth. There is a lot of variation among the countries presented. Northern Nigeria, Northern Ghana, Burkina and Senegal receive cumulatively between 600 and 800 mm of rainfall during the growing period; Mali and Niger on the other hand, see much lower levels of precipitation. Niger cumulatively receives less than 200 mm in the growing period.

For the purpose of our analysis, we selected rainfall or NDVI corresponding to the year before the survey was conducted. In some cases this implied we could observe the impact of particularly negative climatic conditions. For example, Burkina Faso's 2003 EBCVM and DHS were conducted after a severe drop in precipitation in 2002. Likewise, GHS 2012-2013 data have been collected after a particularly dry year for Nigeria (2011). In both cases, nonetheless, the other survey rounds (2010 and 2010-2011) were collected in a relatively favorable period. Overall, this makes the surveys particularly suitable for the resilience analysis we undertake since these surveys contain a negative as well as a positive 'state of the world'.

5.4 NDVI

From space it is possible to observe the surface of the earth and measure the light that is emitted at different wavelengths. Vegetation indexes such as the Normalized Difference Vegetation Index translate visible red and near infrared radiation into a decimal number between -1 and 1 which describes the greenness of a specified geographical area. In order to use NDVI as a proxy for drought, it is common to calculate the anomaly, i.e. the deviation from a long-run average for a specific time of the year.

Predicted NDVI is a composite drought index that is based on greenness anomalies estimated by accumulated rainfall and temperature variations. The measure, explained in more detail in Fisker (2014), uses monthly information on rainfall, temperatures at night and temperatures at daytime to predict NDVI before aggregating to 11 yearly averages. This leads to a satellite based drought-indicator with a spatial resolution of 0.25*0.25 degrees that takes greenness into consideration, but importantly leaves out all anthropogenic causes of change in greenness.

Data on greenness and temperature are obtained from the MODIS Terra satellite. It has been orbiting Earth daily since 2000, and here we employ a pre-processed product made publicly available by NASA that has a temporal resolution of one month and a spatial resolution of 0.05 degrees (3 arc minutes or around 5.8 km at the equator). It is later aggregated to 0.25 degrees in order to match the resolution of the rainfall data and reduce the number of observations. In the end we have a data frame with 1440x720 observations over 180 months.

For each Enumeration area/cluster monthly NDVI is estimated using the four nearest weather data observations with the inverse distances as weights. This way, more weight is put on weather observations, the closer they are to the survey point, and every observation is unique and very precisely estimated.

6 Estimation Results

This section presents the results from our empirical analysis on resilience using consumption and malnutrition measures. Estimated coefficients and residuals will then be used to construct counterfactual outcomes. These outcomes will be compared to (estimated) permanent welfare results, also discussed in this section. Using the taxonomy discussed in section 3, we calculate by country the shares of resilient, non-resilient and chronically poor population. This section concludes by comparing characteristics of these three groups. If the groups are properly defined, we expect the resilient group to show superior characteristics to the other two groups and the non-resilient group to be better off than the chronically poor group.

Consumption models were estimated separately for each country and by pooling different years together. All models use OLS and errors are clustered by country specific macro regions. Tables 2, 3, 4

and 5 show results for Northern Nigeria, Burkina Faso, Senegal and Niger, respectively. Regional dummies and coefficients of interacted variables are not reported. The tables present results for Treated, Control and the full sample. Predicted values from the full sample yield the permanent welfare value. Overall, all models show a high R^2 level, 0.50 in Burkina Faso, 0.40 in Northern Nigeria and Senegal and 0.30 in Niger.

Most of the relevant variables are significant and show the expected signs. Bigger households and higher dependency rates are associated with lower levels of consumption in all countries and in all the specifications. Consumption is positively associated with the educational level of the household head. Completion of higher levels of education (Northern Nigeria, Senegal and Niger) or more years of education (Burkina Faso) is associated with higher levels of consumption per capita. All else being equal, households where the head has a job which is not related to agriculture are better off than those where the head does not have work and those where the head is involved in agricultural work. Accordingly, households where the head is employed in non-agricultural activities have higher per capita expenditure levels. Asset ownership, good quality of housing material and access to protected water and electricity are all positively related with consumption levels in both countries.

In all countries, according to respective year estimates, poverty levels were in the range of 40 to 50 percent. In Burkina Faso, Northern Nigeria, Senegal, one of the data sets was collected after a year when precipitation was below the last decade average. In most of Niger (about 60 percent of clusters) in the specific year analyzed, precipitation levels were lower than the decade average.

Table 6 show the results of weight for age. Country, regional and temporal dummies are not reported but were included in the models. Differently from consumption models, the R^2 level tends to be around 0.20, and more of the dependent variable variance goes unexplained. This has clear consequences on the accuracy of our predictions. On the positive side, as we will see later, the results based on malnutrition are consistent with those based on consumption and more importantly, they reproduce rather accurately the country differences we observed with the consumption models. Furthermore, the relevant variables are significant and show the expected signs. High levels of under-nutrition among children are associated with lower education of the household head, limited access to protected water, flush toilet and electricity and in general limited ownership of assets.

Figure 3 compares the results from the consumption models in Burkina Faso, Northern Nigeria, Senegal and Niger. Niger, Burkina and Northern Nigeria have high percentages of chronically poor: respectively 48, 34 and 27 percent. On the other hand, the chronically poor in Senegal are only 4 percent. The middle group, the non-resilient, is bigger in Senegal and between 38 and 34 percent in the other three countries. Finally resilient households account for about 33 percent in all countries except Niger, where the share falls to 18 percent. Figure 4 presents the results using our other welfare measure, child malnutrition, using the weight for age ratio for 1 to 3 year old children. We find broadly similar patterns as the classification that uses consumption: Senegal has the fewest chronically poor,

while Burkina Faso has the highest. We also find that higher fractions of children in Northern Ghana would be considered resilient to the shocks, while Burkina Faso and Mali have the lowest. Mali, Northern Nigeria and Senegal have large fractions of non-resilient children (those who are neither chronically poor nor resilient).

Is this subdivision by groups meaningful? Are those households we defined as resilient really better equipped to cope with a shock? One simple way we found to test this was to compare, for a number of key characteristics, the mean differences between groups. Households belonging to the resilient group should show, on average, better characteristics than those in the non-resilient group while those in the chronically poor group should be worse than both groups. For simplicity, we report the comparison between the resilient and non-resilient groups[3].

In Tables 7 and 8, we report the group means and t-statistics of their differences, for consumption and in Table 9 for malnutrition. In almost all countries, the resilient group tends to have a smaller household size, fewer dependents, higher levels of education and a higher percentage of quality items. Most of these differences are highly significant as testified by the high values of the t-statistics.

A number of findings are noteworthy. First, our methodology to measure resilience produces rather meaningful results. Provided that the underlying welfare model is accurate, we are able to subdivide households into three different groups (chronically poor, non-resilient and resilient) and the characteristics between these groups are significantly different: resilient households are more educated, own more assets and tend to have less dependents. Second, the results seem to reproduce expected differences between countries. Among the countries analyzed, Niger and Burkina Faso perform worse, when we use consumption. Northern Nigeria performs better than Burkina but worse than Senegal. Finally, and this is probably the most promising part of our work, this analysis can be easily replicated in other countries. Our methodology to test resilience does not require ad hoc data sets, but simply one or more cross section survey rounds and some easily accessible climatic data.

7 Conclusions

The recent experience of the 2010 fuel and food crisis in Sub-Saharan Africa has shown that a single large shock is enough to strain the resilience of plenty of households at once. When such shocks occur in succession and are covariant, that is, affecting an entire region, the consequences are often particularly dreadful for poor households. To worsen conditions, traditional responses that are effective against small-scale shocks are gradually losing momentum, whereas collective responses such as public safety nets are either not available or underfunded and poorly targeted.

[3] Results for group means test between chronic and resilient are available upon request. Differences are almost always significant and non–resilient show better characteristics.

Improving household resilience, therefore, becomes a central issue in any SSA policy agenda, in particular in areas such as the Sahel region, where household exposure to economic and climatic shock is harsh. While conceptualization of resilience has been sharpened over the last years (see for example World Bank, 2014), to our knowledge, efforts to measure resilience have not yet proved fully convincing. Given the urgent need of measuring resilience without waiting for the 'ideal data set', the present paper develops a methodology that uses existing data sets and can already provide some guidance on resilience based on the experience of the last decade. The quantitative measure we provide builds on the idea that a household is resilient if there is very little difference between the pre-shock welfare and the post-shock welfare. This paper contributes to the literature on measuring resilience by providing a method for estimating potential deviation of household income from expected permanent income by using repeated cross sections.

Inspired by the vast literature on counterfactual distributions and survey to survey estimation, we simulated the welfare outcome the household would have experienced if faced with a different state of the world compared to its current state. We first split our survey sample into households or individuals that experienced a shock, those named treated – and those which did not, the control. Next, we estimated separate welfare outcomes for those who received a shock and those who did not. We used these parameters to obtain the counterfactual distributions. The comparison of the permanent welfare level and the counterfactual distributions for each individual indicates who is likely to be resilient and who is not.

The results look promising. Using consumption as a welfare measure in Burkina Faso, Northern Nigeria, Niger and Senegal, we are able to define three distinct groups of households classified on the basis of their resilience. According to these estimates, around 33 percent of households are resilient in three of the four countries. Niger fares much worse, and the resilient group accounts for only 18 percent of the households. The number of chronically poor, those permanently below the poverty line, is around 49 percent in Niger, 33 percent in Burkina Faso, and 26 percent in Northern Nigeria and only 4 percent in Senegal. By contrast, when we look at welfare measures used to analyze the nutritional deficiency of children, we find that resilience levels range from 20 percent in Burkina Faso to 40 percent in Northern Ghana.

In summary, our model offers some potential insights for understanding resilience using only cross sections. In the absence of a panel, two or more cross-sectional household survey rounds linked to rainfall or any available measure of shocks could be enough to obtain a reasonable measure of resilience. This is quite important when deciding on targets for social protection and on scaling up programs to buffer shocks. However, more research is obviously needed to test the robustness of the methodology. In particular, it would be important to validate the model with a panel survey that follows households over several years and at the same time collects information on shocks faced by households, something we plan to do in future research.

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Tables and Figures

Figure 2: Rainfall monthly precipitation (mm) during growing period: 2001-2012

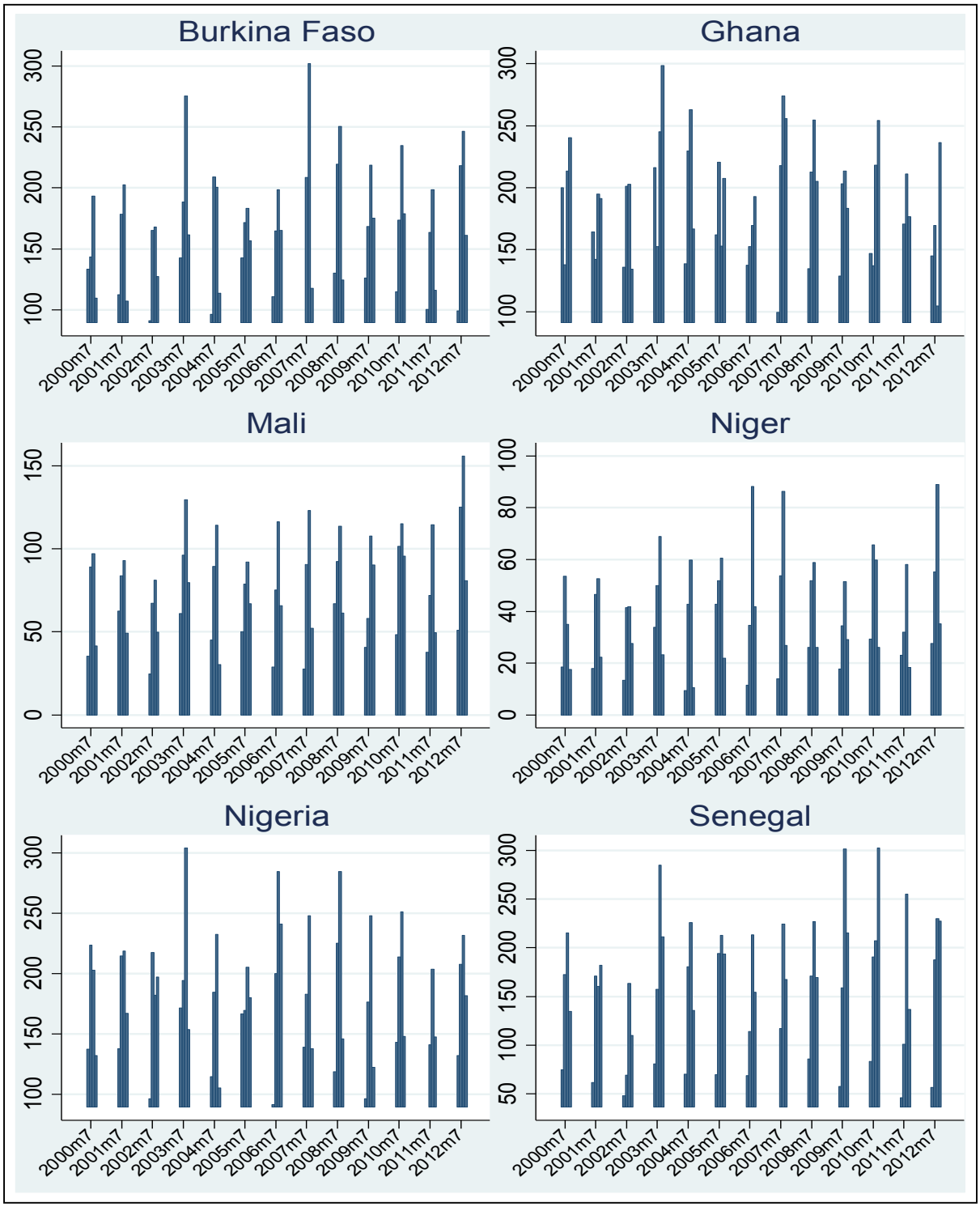
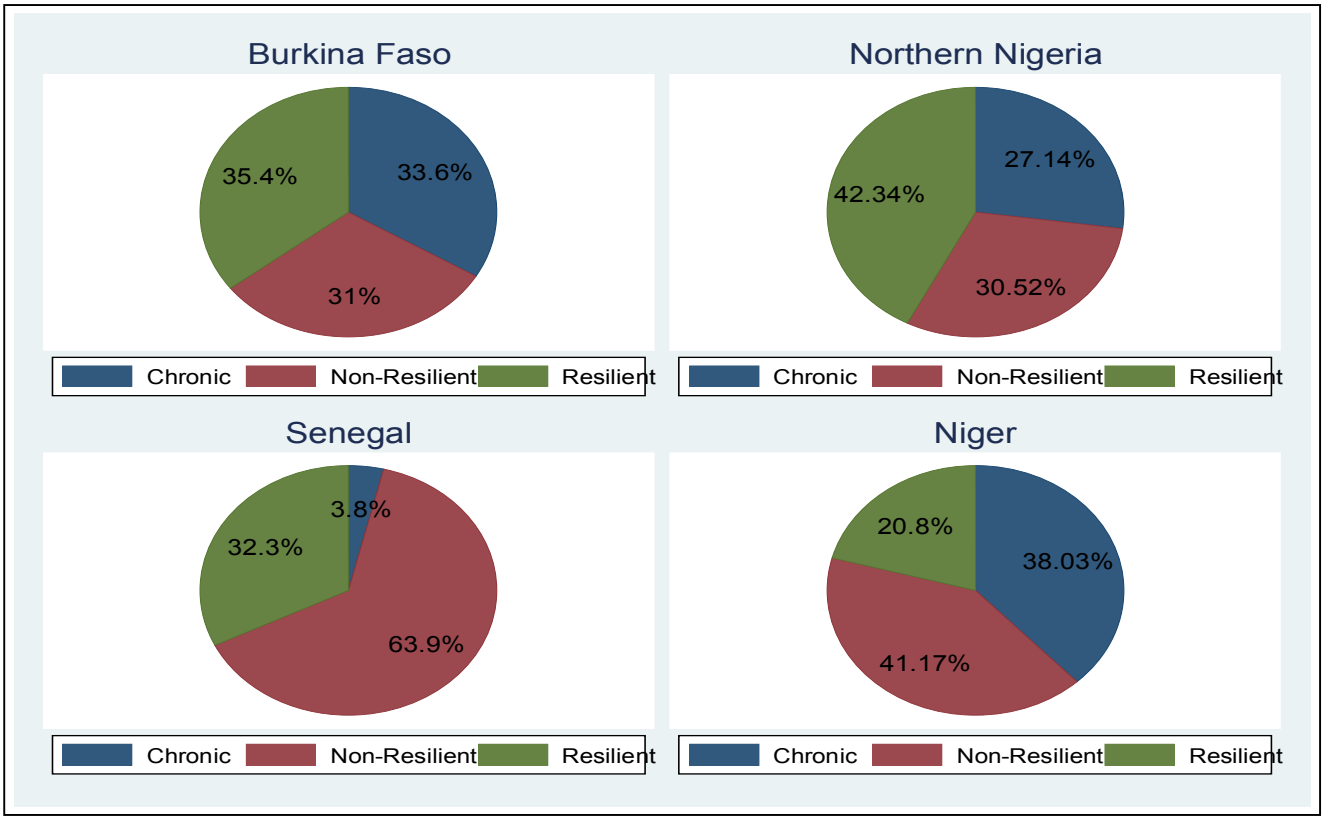
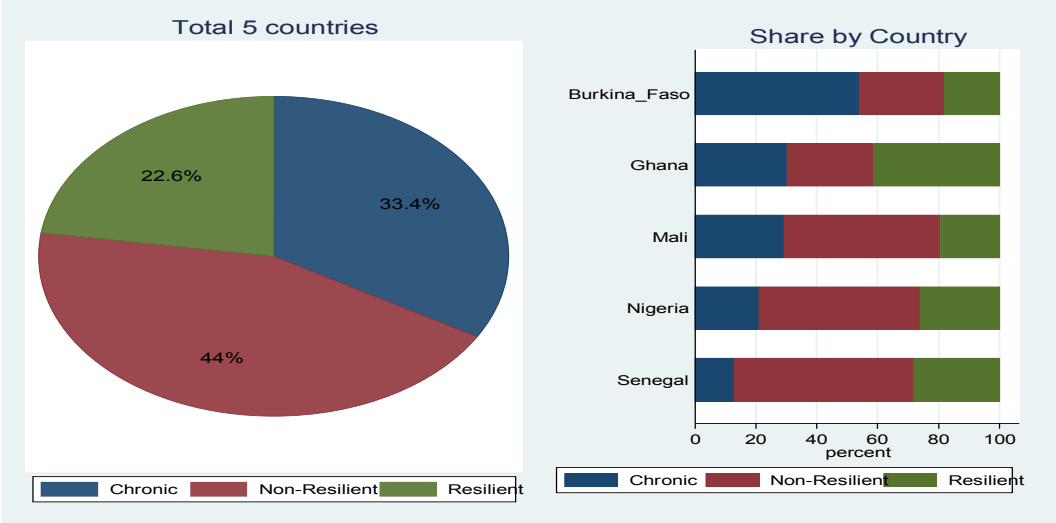


Figure 3: Resilience by country.



Source: Burkina Faso (ESB 2003-2010), Nigeria (GHS-panel 2010-2013), Senegal (ESPS1-2001, ESAM 2005) Niger (ENBC 2005) and authors' calculations

Figure 4: Resilience using Weight for Age



Source: Demographic Health Surveys (several years) and authors calculations

Table 1: Percentage of children wasted (WAZ), acutely malnourished (WHZ) or stunted (HAZ), -2 and -3 standard deviations thresholds

Country	Year	WAZ (<-2)	WAZ (<-3)	WHZ (<-2)	WHZ (<-3)	HAZ(<-2)	HAZ(<-3)
Burkina Faso	2003	0.39	0.15	0.25	0.07	0.33	0.16
Burkina Faso	2010	0.35	0.09	0.19	0.04	0.27	0.09
North. Ghana	2003	0.31	0.10	0.11	0.03	0.33	0.13
North. Ghana	2008	0.23	0.04	0.15	0.02	0.21	0.06
Mali	2006	0.33	0.11	0.18	0.04	0.31	0.14
North. Nigeria	2003	0.35	0.13	0.11	0.03	0.42	0.23
North. Nigeria	2008	0.37	0.15	0.18	0.06	0.44	0.26
Senegal	2005	0.16	0.04	0.10	0.01	0.14	0.03
Senegal	2010	0.23	0.05	0.09	0.01	0.22	0.08

Source: Demographic Health Surveys (various years) and authors calculations

Table 2: Northern Nigeria consumption models

Dependent variable: log real consumption per capita						
	Treated		**Control**		**Permanent**	
	Coeff.	**t**	**Coeff.**	**t**	**Coeff.**	**t**
Number of people in household	-0.009	-0.958	-0.038***	-4.509	-0.021***	-3.326
Population age less than 15 yrs and population aged over 64 yrs	-0.025**	-2.416	-0.018*	-1.859	-0.020***	-2.720
Children between 0 and 4 yrs old	-0.086***	-5.126	-0.046***	-3.032	-0.069***	-6.063
Adult females	-0.009	-0.580	-0.034**	-2.301	-0.018*	-1.645
Nb. of females 65 yrs and above	-0.067**	-2.079	0.037	1.200	-0.023	-1.017
Age of Household head	-0.006*	-1.676	0.007*	1.942	0.000	0.129
Age of household head squared	0.000	0.808	-0.000***	-2.822	-0.000	-1.514

Marital status of HH head	0.087***	5.143	0.114***	7.259	0.102***	8.787
Marital status of HH head==polygamous	-0.070*	-1.754	-0.030	-0.832	-0.052*	-1.915
Sex of Household head	0.011	0.122	0.065	0.722	0.049	0.739
Number of years of education for Household head	0.014***	6.015	0.019***	8.283	0.018***	10.569
Literacy status of household head	0.043	1.281	-0.058*	-1.851	-0.014	-0.601
HH head is self-employed	0.086***	3.466	0.048**	2.312	0.063***	3.894
Sector of activity by broad group of HH head	-0.154***	-4.281	-0.131***	-4.381	-0.150***	-6.511
Ownership of dwelling unit	-0.047	-1.005	0.032	0.751	-0.011	-0.331
Area of residence	0.095***	3.785	0.136***	5.971	0.129***	7.547
Ownership of radio	0.052***	2.788	0.046*	1.939	0.045***	3.020
Ownership of television	0.099***	3.404	0.048	1.318	0.070***	3.072
Ownership of refrigerator	-0.021	-0.600	-0.071*	-1.724	-0.072***	-2.712
Ownership of motorcycle	0.159***	5.225	0.011	0.308	0.088***	3.698
Ownership of sewing machine	-0.080***	-2.917	-0.139***	-4.325	-0.132***	-6.430
Ownership of stove	-0.006	-0.132	-0.049	-0.947	-0.053	-1.485
Ownership of bicycle	0.032	0.990	-0.163***	-4.419	-0.071***	-2.913
Ownership of car	0.043	0.609	-0.168**	-2.374	-0.239***	-5.040
Ownership of generator	0.001	0.010	-0.102	-1.638	-0.075*	-1.811
Ownership of iron	0.099**	2.463	0.118***	2.633	0.093***	3.095
Ownership of fan	0.090*	1.887	0.098	1.635	0.097***	2.585
Ownership of bed or mattress	0.239***	2.739	0.208**	2.530	0.211***	3.464
Main material used for floor - Low quality	-0.066***	-2.596	-0.134***	-5.528	-0.105***	-5.934
Main material used for floor - Medium	-0.157***	-7.825	-0.147***	-7.466	-0.154***	-10.848

quality						
Main source of drinking water - protected	-0.107**	-2.196	-0.054	-1.244	-0.076**	-2.314
Main source of drinking water - unprotected	-0.162***	-3.173	-0.012	-0.267	-0.081**	-2.331
Main cooking fuel - Firewood	-0.323***	-2.698	-0.303***	-3.096	-0.333***	-4.332
Main cooking fuel - Kerosene/oil	-0.179	-1.459	-0.134	-1.332	-0.158**	-1.999
Main cooking fuel - Other	-0.206	-1.581	-0.074	-0.673	-0.159*	-1.877
Main toilet facility - No facility	-0.083*	-1.862	-0.194***	-4.894	-0.146***	-4.845
Main toilet facility - Flush toilet	0.322***	3.602	0.545***	6.502	0.514***	8.335
Constant	11.746***	50.488	11.608***	57.898	11.644***	77.217
R2	0.421		0.467		0.417	
Observations	4,828		4,982		9,810	

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 3: Burkina Faso consumption models

Dependent variable: log real consumption per capita						
	Treated		**Control**		**Permanent**	
	Coeff.	**t**	**Coeff.**	**t**	**Coeff.**	**t**
Household members	-0.095***	-18.886	-0.051***	-7.929	-0.076***	-19.126
Sex of household head	-0.062**	-2.074	0.026	0.735	-0.016	-0.720
Age of household head	-0.001	-1.108	-0.002**	-2.153	-0.001***	-2.842
Dependency ratio	-0.086***	-13.385	-0.065***	-8.391	-0.080***	-16.114
head is widowed	-0.166***	-3.620	-0.060	-1.188	-0.112***	-3.269
Number of children <=4 yrs old	0.158***	5.782	-0.035	-1.211	0.070***	3.488
Number of children <=5 yrs old	-0.039	-1.594	0.066***	2.711	0.012	0.709
Number of children 5-10 yrs old	0.058***	4.567	-0.042***	-3.043	0.014	1.555
Number of girls 11-14 yrs old	0.033*	1.812	-0.061***	-3.078	-0.004	-0.279
Number of females 15-19 yrs old	-0.010	-0.599	-0.059***	-2.811	-0.035***	-2.669
Number of females 20-34 yrs old	0.045***	2.812	0.030	1.473	0.033***	2.625
Number of females 35-59 yrs old	0.009	0.514	-0.004	-0.201	-0.001	-0.104
Number of females >=60 yrs old	0.022	0.883	-0.040	-1.468	-0.004	-0.207
Literate household head (1=yes)	0.039	0.871	0.210***	3.451	0.076**	2.545
Head has primary education	0.082	1.502	0.080**	2.090	0.064**	2.072
Head has secondary education	0.059	0.679	-0.077	-0.938	0.036	0.710
Head has higher education	0.384***	5.075	0.156	1.151	0.334***	5.664
Head is employed in the public sector	0.014	0.283	0.305***	3.733	0.072*	1.739
Head is self-employed	-0.022	-0.540	0.179***	3.277	0.067**	2.053
Head is self-employed in agriculture	-0.212***	-4.718	-0.163***	-3.729	-0.227***	-7.532
Head is caregiver/volunteer	-0.101	-0.909	0.168	1.613	0.019	0.254

Head is unemployed	-0.052	-1.130	-0.075	-0.299	-0.023	-0.555
Head is inactive	-0.152	-1.567	-0.151**	-2.542	-0.184***	-3.824
Dwelling has good wall	-0.007	-0.158	0.203***	3.276	-0.092***	-5.502
Dwelling has good roof	0.006	0.226	0.092***	3.073	0.061***	2.929
Dwelling has sand or smoothed mud floor	-0.191***	-6.367	-0.097***	-3.304	-0.148***	-7.113
HH has electricity	0.338***	8.327	0.324***	6.062	0.360***	11.191
HH has any toilet	0.542***	8.247	0.327*	1.731	0.499***	8.136
HH owns motorcycle	0.282***	10.132	0.351***	12.493	0.323***	16.178
HH owns bicycle	-0.039	-1.529	-0.035	-1.099	-0.042**	-2.103
HH owns television	0.240***	5.617	0.100**	2.136	0.171***	5.392
HH owns plow	0.093***	3.910	0.019	0.737	0.040**	2.294
Constant	12.571***	188.302	12.247***	142.009	12.431***	264.661
R2	0.475		0.488		0.461	
Observations	11,227		5,753		16,980	

note: *** p<0.01, ** p<0.05, * p<0.1

Table 4: Senegal consumption models

Dependent variable: log real consumption per capita						
	Treated		**Control**		**Permanent**	
	Coeff.	**t**	**Coeff.**	**t**	**Coeff.**	**t**
Gender of the head==male	0.145***	7.690	0.101***	3.797	0.153***	9.990
Household size	-0.030***	-13.739	-0.042***	-10.539	-0.028***	-15.533
Head is married	0.072***	3.490	0.059*	1.897	0.077***	4.432
Head is single	0.109***	2.642	0.142**	2.518	0.118***	3.529
Head is female single	0.018	0.185	-0.050	-0.368	-0.025	-0.323

Number of children <=4 yrs old	-0.019	-1.525	-0.025	-1.356	-0.026**	-2.428
Number of children <=5 yrs old	0.012	1.065	0.019	1.195	0.016*	1.706
Number of children 5-10 yrs old	-0.015***	-2.653	-0.013	-1.515	-0.019***	-3.996
Number of females 15-19 yrs old	-0.029***	-3.755	-0.011	-0.963	-0.030***	-4.781
Number of females 20-34 yrs old	-0.005	-0.866	0.022**	2.149	-0.007	-1.406
Number of females 35-59 yrs old	-0.023***	-2.762	0.019	1.437	-0.025***	-3.721
Number of females >=60 yrs old	-0.002	-0.153	0.029*	1.650	0.002	0.216
Age of the head	-0.001	-1.622	0.000	0.275	-0.000	-0.593
Dependency ratio	-0.098***	-12.396	-0.096***	-8.180	-0.099***	-14.987
Primary education	0.018	1.105	0.049**	2.023	0.041***	2.938
Secondary education	0.161***	8.468	0.064**	2.331	0.143***	9.043
Higher education	0.421***	12.028	0.185***	4.139	0.354***	12.799
HH owns electric iron	0.009	0.193	0.154***	3.334	0.050	1.544
HH owns refrigerator	0.165***	7.944	0.220***	8.712	0.180***	11.189
HH owns radio	0.018	1.006	0.196***	8.512	0.063***	4.480
HH owns watch or alarm	0.185***	12.016	0.056***	3.148	0.127***	10.914
HH owns sewing machine	0.125***	3.981	0.016	0.410	0.078***	3.124
HH owns modern stove	0.044	1.100	0.029	0.466	0.050	1.471
HH owns bicycle	0.056**	2.119	-0.042**	-2.049	-0.018	-1.138
HH owns motorcycle	0.185***	5.656	0.158***	5.717	0.167***	7.916
HH owns car or truck	0.290***	8.167	0.306***	6.473	0.295***	10.325
HH owns television	0.184***	10.287	0.241***	11.146	0.202***	14.632
Household has any toilet	0.241***	17.773	0.244***	10.730	0.248***	21.203
Constant	12.283***	243.349	11.842***	160.896	12.146***	292.135
R2	0.407		0.452		0.410	
Number of observations	10,452		4,783		15,235	

note: *** p<0.01, ** p<0.05, * p<0.1

Table 5: Niger consumption models

Dependent variable: log real consumption per capita						
	Treated		**Control**		**Permanent**	
	Coeff.	**t**	**Coeff.**	**t**	**Coeff.**	**t**
Age of HH head	0.001	1.500	-0.003**	-2.281	0.000	0.298
Gender of HH head	-0.078*	-1.950	-0.118*	-1.711	-0.090***	-2.598
Household size	-0.073***	-9.096	-0.051***	-3.938	-0.068***	-10.021
Head is female single	0.127	0.510	0.643	1.120	0.211	0.937
Head is single	0.382***	4.771	0.324**	2.252	0.364***	5.230
Number of children <=4 yrs old	0.006	0.229	-0.030	-0.774	-0.002	-0.091
Number of children <=5 yrs old	-0.028	-1.290	-0.024	-0.701	-0.028	-1.547
Number of children 5-10 yrs old	-0.017	-1.316	-0.051**	-2.508	-0.024**	-2.244
Number of females 15-19 yrs old	0.057***	2.756	0.006	0.195	0.046***	2.628
Number of females 20-34 yrs old	0.044**	2.284	-0.001	-0.036	0.034**	2.058
Number of females 35-59 yrs old	0.032	1.318	0.014	0.374	0.026	1.285
Number of females >=60 yrs old	-0.015	-0.456	0.037	0.713	-0.001	-0.025
Head has primary education	0.024	0.652	-0.016	-0.332	0.008	0.279
Head has secondary education	0.144**	2.559	0.032	0.392	0.107**	2.313
Head has higher education	0.080	0.938	0.306***	2.611	0.155**	2.264
Head is unemployed	0.202***	2.898	0.019	0.225	0.134**	2.475
Head is employed in the private sector	0.118	1.064	0.096	0.579	0.092	0.999
Head is employed in the public sector	0.077	1.003	0.054	0.534	0.050	0.824
Head is self-employed in agriculture	0.018	0.302	0.051	0.340	0.023	0.423
Dwelling has good roof	0.055**	2.329	0.025	0.736	0.047**	2.404
HH has electricity	0.116**	2.235	0.244***	3.226	0.158***	3.696
HH has piped or protected water source	-0.041**	-1.999	-0.050	-1.524	-0.042**	-2.443
HH has any toilet	0.239***	3.276	0.028	0.389	0.128**	2.507

HH owns car	0.491***	3.790	0.300**	2.172	0.417***	4.389
HH owns motorcycle	0.299***	5.769	0.284***	3.286	0.301***	6.801
HH owns bicycle	0.002	0.054	0.112*	1.929	0.029	0.965
HH owns refrigerator	0.059	0.649	0.063	0.535	0.027	0.383
HH owns stove	0.208**	2.047	0.034	0.263	0.124	1.616
HH owns television	0.072	1.095	0.191**	2.276	0.113**	2.180
HH owns radio	0.161***	8.010	0.095***	3.038	0.146***	8.604
HH owns foyer	0.230***	10.634	0.237***	6.343	0.231***	12.390
Constant	12.171***	198.775	12.041***	21.466	12.247***	234.458
R2	0.270		0.396		0.310	
Number of observations	4,220		1,449		5,669	

note: *** p<0.01, ** p<0.05, * p<0.1

Table 6: Weight for age modules in 5 countries (Burkina Faso, Northern Nigeria, Mali, Northern Ghana and Senegal)

Weight for age						
	Treated		**Control**		**Permanent income (Pooled sample)**	
	coef	**t**	**coef**	**t**	**coef**	**t**
number of household members	-0.008***	-2.889	-0.011***	-4.299	-0.010***	-5.480
Male headed HH	0.021	0.444	-0.034	-0.795	-0.014	-0.429
Age of HH head	0.002	1.568	0.001	0.901	0.001*	1.790
current age of child	0.120***	2.646	0.033	0.788	0.043	1.403
Primary education	0.203***	5.716	0.141***	3.983	0.184***	7.350
Secondary education	0.416***	8.420	0.361***	7.413	0.400***	11.529
Higher education	0.536***	3.999	0.642***	4.862	0.585***	6.204
water_good	0.039	1.476	-0.025	-0.806	0.003	0.161
HH has toilet	0.012	0.437	0.066**	1.980	0.027	1.287
HH has electricity	0.016	0.367	0.052	1.151	0.021	0.663
HH has radio	0.044*	1.657	0.054*	1.765	0.056***	2.777
HH has TV	0.140***	3.286	0.123***	2.953	0.131***	4.378
HH has refrigerator	0.025	0.390	0.249***	4.017	0.132***	2.938
HH has bicycle	-0.099***	-3.555	-0.101***	-3.300	-0.100***	-4.895

HH has motorcycle	0.032	1.124	0.018	0.599	0.027	1.306
HH has car	0.206***	3.036	0.126*	1.842	0.171***	3.544
HH has phone	0.109	1.387	0.035	0.500	0.075	1.414
Dwelling has good floor	0.074**	2.558	0.149***	4.648	0.108***	5.128
wall_good	-0.000	-0.006	-0.022	-0.637	-0.001	-0.025
roof_good	0.025	0.549	-0.073**	-1.998	-0.002	-0.070
_cons	0.322**	2.368	-0.020	-0.044	0.053	0.618
F	89.954		53.039		140.002	
R2	0.234		0.197		0.215	
Number of observations	14,165		10,419		24,584	
note: *** p<0.01, ** p<0.05, * p<0.1						

Table 7: Group means statistical differences for Northern Nigeria and Burkina Faso

Northern Nigeria				Burkina Faso			
Variable	**Non resilient**	**Resilient**	**t-statistics**	**Variable**	**Non resilient**	**Resilient**	**t-statistics**
Household members	5.63	5.65	-0.29	Household members	5.16	5.12	0.73
Sex of HH head	0.93	0.93	-0.87	Sex of HH head	0.90	0.88	2.55
Dependency ratio	2.60	2.60	-0.02	Dependency ratio	1.67	1.48	8.20
Years of education	6.35	5.96	2.85	Completed primary education	0.13	0.20	-8.77
Literacy status of the HH head	1.36	1.38	-1.69	Completed secondary education	0.09	0.06	4.58
HH head employed in private sector	0.68	0.71	-2.11	Completed higher education	0.02	0.05	-8.59
HH head employed in agriculture	0.48	0.52	-3.12	HH head employed in agriculture	0.62	0.49	13.96
Low quality floor	0.14	0.13	1.13	Dwelling has good wall	0.26	0.66	-46.23
Medium quality floor	0.20	0.25	-5.13	Dwelling has good roof	0.78	0.80	-2.99
Unprotected water source	0.43	0.47	-3.45	Dwelling has sand floor	0.56	0.41	15.86
Cooking with wood	0.85	0.89	-5.04	Dwelling has electricity	0.16	0.28	-14.62
Dwelling has no toilet	0.24	0.21	2.69	Owning motorcycle	0.35	0.42	-7.34
Owning motorcycle	0.44	0.56	-9.99	Owning bicycle	0.75	0.70	5.84
Owning car	0.13	0.35	-21.75	Owning television	0.17	0.26	-11.19
Owning bicycle	0.25	0.49	-20.45				
Owning television	0.36	0.50	-11.97				

Table 8: Group means statistical differences for Senegal and Niger

Senegal				Niger			
Variable	**Non Resilient**	**Resilient**	**t-statistics**	**Variable**	**Non Resilient**	**Resilient**	**t-statistics**
Household members	9.39	8.49	9.74	Household members	4.61	4.95	-3.66
Dependency ratio	1.16	1.01	10.25	Completed primary education	0.09	0.12	-2.30
Completed primary education	0.12	0.15	-4.72	Completed secondary education	0.04	0.10	-5.56
Completed secondary education	0.09	0.15	-10.63	Completed higher education	0.04	0.07	-2.74
Completed higher education	0.03	0.03	-1.12	HH head is self-employed	0.76	0.65	6.04
Owning iron	0.02	0.03	-4.58	HH head employed in agriculture	0.02	0.03	-2.67
Owning refrigerator	0.11	0.20	-14.29	Roof in good conditions	0.88	0.64	15.78
Owning mattress	0.54	0.91	-46.37	Electricity	0.11	0.16	-3.99
Owning radio	0.48	0.78	-35.03	Protected water	0.68	0.51	9.60
Owning watch	0.37	0.50	-15.01	Dwelling has toilet	0.02	0.07	-6.53
Owning motorcycle	0.04	0.06	-4.88	Owning car	0.01	0.03	-3.71
Owning car	0.02	0.04	-8.36	Owning motorcycle	0.06	0.08	-1.53
Owning television	0.20	0.34	-18.25	Owning bicycle	0.07	0.15	-7.14
Dwelling has toilet	0.20	0.40	-25.03	Owning refrigerator	0.02	0.07	-6.43

Table 9: Group mean statistical differences for weight for age measures, by country

	Burkina Faso			**Ghana**			**Mali**		
	Non-resilient	Resilient	t-statistic	Non-resilient	Resilient	t-statistic	Non-resilient	Resilient	t-statistic
HH size	8.29	8.60	-1.76	7.59	6.74	3.42	7.04	7.66	-4.95
Edu. prim	0.16	0.16	0.50	0.19	0.13	2.34	0.12	0.15	-2.25
Edu seco	0.10	0.10	-0.04	0.08	0.13	-2.27	0.08	0.08	-0.24

Edu. high	0.00	0.01	-0.79	0.00	0.03	-2.32	0.00	0.01	-0.73
Electricity	0.14	0.16	-1.48	0.13	0.23	-3.39	0.17	0.25	-6.46
Own tv	0.19	0.18	0.41	0.09	0.16	-2.75	0.28	0.36	-5.04
Own car	0.02	0.03	-1.51	0.01	0.01	-0.20	0.05	0.05	-0.65
Floor good	0.47	0.53	-3.50	0.65	0.79	-4.16	0.26	0.35	-5.88
Wall good	0.33	0.25	5.05	0.19	0.22	-1.05			
Roof good	0.32	0.24	5.79	0.30	0.27	1.09			

	Northern Nigeria			**Senegal**		
	Non-resilient	Resilient	t-statistic	Non-resilient	Resilient	t-statistic
HH size	7.47	7.73	-1.94	13.38	14.62	-4.30
Edu. prim	0.28	0.22	4.10	0.23	0.22	0.56
Edu seco	0.21	0.18	2.40	0.08	0.08	-0.84
Edu. high	0.04	0.04	-1.25	0.00	0.00	0.15
Electricity	0.30	0.43	-8.07	0.40	0.40	-0.09
Own tv	0.27	0.33	-4.59	0.40	0.40	-0.32
Own car	0.09	0.10	-1.33	0.05	0.05	-0.58
Floor good	0.51	0.53	-1.49	0.56	0.56	0.39
Wall good	0.46	0.38	4.68	0.38	0.45	-3.66
Roof good	0.55	0.45	6.36	0.36	0.46	-5.78