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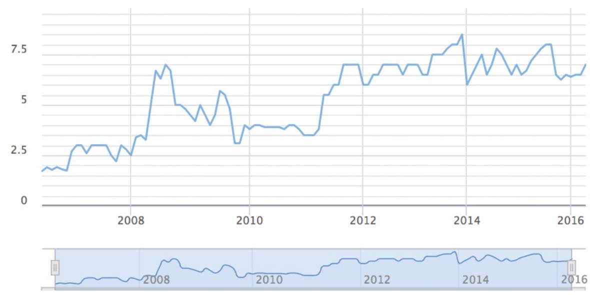
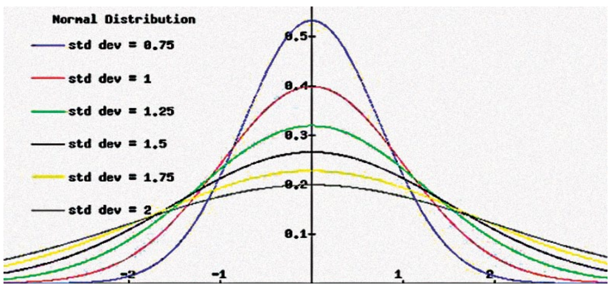
Quantitative Analyses for Resilience Measurement

GUIDANCE FOR CONSTRUCTING VARIABLES AND EXPLORING RELATIONSHIPS AMONG VARIABLES





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August 2016

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Acknowledgements

As part of the effort to advance resilience measurement, this paper on quantitative analysis for resilience measurement is one of a series of technical products developed under the auspices of the Food Security Information Network's (FSIN) Resilience Measurement Technical Working Group (RM-TWG), with overall coordination provided by RM-TWG Chair, Mark Constas. It was prepared jointly by Marco d'Errico (FAO), Alessandra Garbero (IFAD) and Mark Constas (Cornell University).
This paper, which reflects the deliberations of the RM-TWG as a whole, elaborates on concepts presented in Technical Series Nos. 1 and 2 regarding quantitative analysis for resilience measurement. It was kindly reviewed by RM-TWG members Arif Husain (Chief Economist and Deputy Director, Policy, Programme and Innovation Division, WFP) and Luca Russo (Senior Economist, Agriculture Development Economics Division, FAO).

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Abbreviations

FAO	Food and Agriculture Organization of the United Nations
FSIN	Food Security Information Network
IFAD	International Fund for Agricultural Development
MIMIC	Multiple Indicator Multiple Causes Model
PCA	Principal Component Analysis
RM TWG	FSIN's Resilience Measurement Technical Working Group
SEM	Structural Equation Model
WFP	World Food Programme

I. Background

Climate change dynamics, unexpected disease outbreaks, widespread social unrest and political conflict, and volatility in food prices have changed the risk landscape for the world's poor. Recognizing this, the concept of resilience has captured the interest of donors, policymakers and implementers who work to address problems of food security, poverty and a broader set of welfare outcomes. The international community, spanning both development assistance and humanitarian aid, has devoted large amounts of funding to financing programmes and policies aimed at enhancing the resilience of individuals, households, livelihoods, communities, markets and the often fragile food systems on which the poor depend. Consequently, the number of programmes and interventions directed at building resilience has increased greatly over the past few years. Recognizing that the final value of this growing body of work on resilience will be settled through empirical study, the Resilience Measurement Technical Working Group (RM-TWG) was formed to offer guidance on sound measurement practices.

As the foundation for empirical work on resilience, measurement involves a set of methods that translate abstract concepts into quantitative representations (e.g. indicators, variables, scales or models). Based on accepted procedures from econometrics and statistics, quantitative methods for resilience measurement may be described using two estimation frameworks. The first is concerned with resilience as a variable. The associated analysis methods address the question *"What procedures can be used to define the set of indicators that represent resilience?"* The second estimation framework examines relationships in which resilience is a key variable. Analysis methods for this framework address the question *"How can we model and test the way in which resilience is part of a relationship?"* With these frameworks and questions in mind, the objective of this RM-TWG technical briefing is to present some of the quantitative methods that may be used in resilience analysis.

Section 2 of this briefing comprises a short discussion of the importance of defining resilience clearly. The following two sections explore the questions associated with the two estimation frameworks, offering a series of guiding principles and, where appropriate, formulaic expressions. Section 5 contains a few observations on data requirements. This briefing is deliberately concise; for detailed explanations of the more technical aspects of resilience measurement, please consult the list of resources provided at the end of the paper, where there is also a glossary of terms.

II. Defining Resilience: Fundamental Precursor to Measurement

The provision of a clear, concise, readily operationalized definition of what is to be measured is at the foundation of sound measurement. A notable accomplishment of the RM-TWG, formed by FSIN in 2013, was that it was able to reach consensus on a definition of resilience. The working group's first paper defines resilience as the *"capacity that ensures stressors and shocks do not have long-lasting adverse development consequences"* (Constas, Frankenberger and Hoddinott 2014, 4). From an analytical perspective, this definition locates resilience on the right-hand side of a model, as an independent variable, one of several that may predict some development consequence (i.e. well-being outcome) such as food security or poverty.

While the definition adopted by the RM-TWG suggests that resilience is important as a predictor of well-being in the face of shocks and stressors, there are other ways to define resilience.[1] Because the goal of the present briefing is to provide broadly applicable guidance on quantitative analysis for resilience measurement, it is useful to consider definitions beyond the one offered by the RM-TWG.

A cursory review of work on the subject reveals four current versions of resilience. First, resilience as a capacity can be defined as a variable that is predicted, explained or constructed by a selection of other variables. Second – and consistent with the RM-TWG definition – resilience (once constructed as a variable) may be defined as a capacity that predicts well-being in the face of shocks. Third, resilience can be defined as the property (i.e. observed change over time, return time) of a well-being outcome. Fourth, resilience is used by some as an approach strategy, one that may be used to frame problems and/or structure policies and interventions. Table 1 presents each of these definitions along with a simple statistical expression. For empirical work, the terms in the expressions would be populated with the data and relationships modelled.[2]

Table 1. Different definitions of resilience and simple statistical expressions

Version of Resilience	Associated Definition of Resilience	Statistical Expression
Resilience as a multidimensional construct	Resilience is a capacity explained by or composed of multiple dimensions	RC = f (d1, d2, d3.....)
Resilience as a predictor	Resilience is a capacity that predicts well-being in the face of shocks and stressors (static measure)	WB = f (RC, SS, CV)
Resilience as a property	Resilience is the property of some well-being outcome observed over time (dynamic measure)	$WB^{t1...i}$ = f (RC, SS, CV)
Resilience as a paradigm	Resilience is an overarching approach or paradigm used to frame a problem	N/A

RC = resilience capacity f = function of d = dimension WB = well-being outcome SS = shocks and stressors
CV = covariates t = time 1...i superscript = measurements taken at various points in time.

The first version of resilience corresponds with estimation frameworks for constructing resilience variables (see section 3). Versions two and three correspond with estimation frameworks for examining relationships (see section 4). Version four is more paradigmatic than statistical or econometric; it has no immediate corresponding statistical form and is therefore not included in this briefing.

1. The four definitions of resilience and the contents of Table 1 are adapted from M. Constas, *The Four Versions of Resilience for Development: Implications for programming and measurement.* Manuscript in preparation: FSIN.
2. It is reasonable to assume that resilience capacity may be correlated with other explanatory variables and/or with measurement error. When using resilience capacity as an explanatory variable, potential problems of endogeneity should therefore be considered and diagnosed (e.g. using the Durbin-Wu-Hausman test of endogeneity).

III. Estimation Frameworks for Constructing Variables that Represent Resilience

An initial stage of quantitative methods for measurement involves using a set of analytical tools to translate concepts into numerical form. The question posed here is *"What procedures can be used to define the set of indicators that represent resilience?"* Answering this question requires estimating a measure of the resilience capacity of a specific unit (e.g. a household, community or system) at a certain point in time. Estimation procedures used to construct resilience variables should be based on the following analytical principles:

- Resilience multidimensionality
- Resilience as a latent variable or as an observed variable
- Resilience as an index

Brief descriptions for each of these principles are provided below.

Resilience Estimated as a Multidimensional Variable

Like many variables measured in studies of poverty and food security, resilience is multidimensional (see Alkire and Foster 2011). This means that resilience must be considered as a function of a number of dimensions (D) or characteristics that can be context and time-specific (FAO 2015; Constas et al. 2014b). When constructing variables, consider the following principle:

> **Multidimensionality Principle:** Resilience is comprised of various dimensions. The selection of dimensions used to estimate resilience should be informed by empirical work, theory and programmatic contexts

As a simple statistical expression, the following shows how resilience may be comprised of a number of dimensions.

$$R_{i,t} = f\,(D_1, D_2, \ldots, D_n) \tag{1}$$

R = Resilience
I = given case or observed unit (e.g., household)
t = a given time
D = dimension that constitutes resilience

Resilience Estimated as a Latent Variable

The method used to identify the dimensions that make up resilience is not arbitrary. The capacities and characteristics that represent resilience may not be observable; this leads to the second principle that has implications for how resilience variables might be estimated.

> **Resilience is a latent concept:** Resilience cannot be measured directly, at least not under the assumption of multidimensionality. It can, however, be indirectly measured with an underlying structure. This assumption, and related assumptions about measurement, should be clearly stated.

If resilience is a latent variable, we cannot observe – and, consequently measure – resilience directly. However, we can represent resilience as clusters of indicators and look at each of the n clusters separately.

Thus, if we relax the multidimensionality assumption and consider just a sub-set m of the n clusters, it is possible to hypothesize a measure of resilience which includes 1 to *m* (where $m<n$) clusters. Under the extreme assumption of the mono-dimensionality of resilience, it is therefore possible to estimate resilience directly. However, this dramatically reduces the scope of a resilience analysis and, in fact, there are few examples of mono-dimensional measurement of resilience.

Resilience Estimated as an Index

Different procedures have been proposed to aggregate the various dimensions of resilience into one single measure: a resilience index. There are advantages to using an index to represent a complex multidimensional construct: it allows for more concise description and it may facilitate comparability, ranking, targeting and aggregation across settings. An index is also easily incorporated into other modelling procedures.

> **Resilience Aggregation Principle:** Resilience may be measured and represented as a composite that constitutes an index. The (conceptual or computational) decision to use an index or individual variables should be explained, both conceptually and statistically.

Indices are not always readily accepted, but using an index does not necessarily preclude the use of individual variables. For example, we could measure resilience as an index and then investigate the way in which individual variables and/or indicators explain heterogeneity observed in the index itself.

If resilience is to be conceived as a multidimensional index,[3] an aggregative procedure should be defined. There are two broad categories of aggregative procedure: those that seek to explain the role of each variable when defining the final index, and those that do not. The most commonly used procedures in the former group are multivariate models; the latter typically adopt a moment-based approach.[4]

3. Although other non-aggregative approaches exist for measuring resilience.

4. This group of measures adopted as proxies for resilience originates from Barrett's recognition of the existence of a non-linear relationship among assets, shocks and income growth in the context of the study of poverty dynamics (Barrett and Carter 2005). This approach has been further developed by Barrett and Constas (2014) into a more general theoretical framework for resilience based on stochastic well-being dynamics; it has also been recently translated into a moment-based approach (Cissé and Barrett 2015) in order to create an aggregate measure of resilience.

   The moment-based approach, originally developed by Hansen (1982) in econometrics, has been applied to multidimensional poverty or poverty analyses since 2003 (Atkinson 2003; Duclos, Sahn and Younger 2005; Esposito and Chiappero Martinetti 2008). In their paper, Cissé and Barrett (2015) develop Foster, Greer and Thorbecke (Foster et al. 1984) equivalent indices of resilience. This approach is an interesting alternative to the aggregation procedures presented thus far. It enables the development of a decomposable resilience indicator that aggregates household-specific probabilities across the population of interest into a single measure. The drawback of such an approach is that no evidence is provided with regard to the role of each variable in determining resilience.

Factor analysis is used to estimate a construct that is not directly observed (Bollen 2002) – in this case, resilience. It reduces a set of observed variables used as proxy indicators for the latent variable into a single variable, the component of interest. The data reduction mechanism relies on finding cross-correlations between the observed variables, identifying the number of (unobservable) factors reflected in the correlations, and predicting the latent outcome as a linear combination of underlying factors. If all the variables defining the latent variable are closely correlated, they may be represented by a single factor. When variables cluster into a few groups of closely related variables, they can be represented by more than one factor. The number of factors should be chosen so that at least 90 percent of the total variability is explained.

The basic idea of a latent variable approach for resilience measurement is that "there are one or more latent variables that create the association between unobserved variables" (Bollen 2002, 609). A formal expression of this idea is as follows (Ibid., 623):

$$Y_i = \lambda_0 + \lambda_1\xi_{i1} + \lambda_2\xi_{i2} + \cdots + \lambda_K \xi_{iK} + u_i \tag{2}$$

Where:

Y_i = observed indicator for the i^{th} case

λ_0 = intercept term

$\xi_{i1} \ldots \xi_{ik}$ = factor loadings for 1st through *k* case

u_i = unique variable or error term

If resilience is viewed as directly with no underlying structure, principal component analysis (PCA) may be used. PCA is a data reduction technique that can be adopted to reduce the dimensionality of a dataset by finding a new set of variables, called 'principal components', which are uncorrelated, retain most of the sample information and are ordered by the fraction of the total information that each component explains. PCA can also be used to reduce the number of variables that enter a regression analysis by isolating the most relevant ones. However, it cannot be employed to create a latent variable that is linearly correlated with the underlying dimensions, as PCA does not consider linear relations during the estimation process. In addition, PCA is computed without assuming any underlying structure in the data; components are calculated using the variance of the observable variables, and the total variance appears in the solution (Costello and Osborne 2005). The method takes into consideration not only the variance of variables that can be attributed to the latent factor, but also that part of variance which is uniquely attributable to the variable itself (the so-called uniqueness).

Structural Equation Models (SEMs) are used to measure covariates among observed variables and correlations among dimensions (Acock 2013, Bollen et al. 2007). SEM combines factor analysis with regression. It is assumed that the set of measured variables is an imperfect measure of the latent variable of interest. SEMs use a factor analysis-type model to measure the latent variable via observed variables, while simultaneously using a regression-type model to identify relationships among the underlying variables (Bollen 1989). Generally, the estimation methods developed for SEMs are limited to the normally distributed observed variables, but in most cases (including resilience), many variables are nominal or ordinal. Attempts have been made to broaden SEMs to include nominal/ordinal variables, but there are difficulties regarding computational aspects (Muthén 1984). It is also possible to use generalized latent variable models (Bartholomew and Knott 1999, Skrondal and Rabe-Hesketh 2004) to model different response types. A major concern in using SEMs for measuring resilience is that the algorithms of SEM procedures are usually totally data driven.

It is important to stress that, unlike SEMs, factor analysis assumes that the residual errors (i.e. unique factors) are uncorrelated with each other and with the common (i.e. latent) variable. These assumptions rarely hold in reality, particularly in a framework where resilience is indexed to an outcome such as food security or well-being. In these instances, the probability of intra-dimensional correlation is high. Therefore, SEMs tend to be the preferred estimation frameworks for resilience as they include correlation among residual errors and allow for a number of goodness-of-fit tests. Although SEMs require a greater computational effort compared with factor analysis, they can be calibrated until a satisfactory level of goodness-of-fit is achieved.

Within SEMs, one approach is to use Multiple Indicator Multiple Causes (MIMIC) models. These are causal models which allow one latent variable with multiple underlying indicators and multiple causes. SEMs (and therefore MIMICs) have two measurement models: formative and reflective (Edward and Bagozzi 2000). A reflective model sees a latent variable as the cause of observed variables; the formative model sees the observed variables as the causes of a latent variable model. In the linear version of the MIMIC, the relationship between the latent variable and its causes – and between the indicators and the latent variable – are linear in the parameters. In the MIMIC model, the dependent variable (which is regressed on the formative indicators) is the shared variance of the reflected variables or constructs. The error term, then, is the shared variance between the outcomes (i.e. the two or more reflective components) not accounted for by the formative indicators (Wilcox et al. 2008, 1224). Typically, MIMIC models are adopted to understand measurement invariance and heterogeneity (Flora and Curran 2004). They are mainly employed in psychometrics and social science. They are strong candidates for resilience analysis because they can provide useful information about the interaction between outcome variables and between outcome variables and each individual resilience dimension.

IV. Estimation for Exploring Resilience Relationships

In this section, resilience is viewed as instrumental to the study of another phenomenon or outcome of interest. It feeds into a broader scope analysis (food security, poverty or more generally, well-being). Thus, a theoretical model of the phenomenon of interest needs to be formalized so it can be subject to rigorous empirical examination.

- Resilience formalization principle
- Resilience path-dependence principle
- Resilience as a non-linear relationship principle
- Resilience as a hierarchical context-dependent principle

A brief description of each of these principles is provided below. Examples of how they are put into practice are noted in footnotes with links to documents listed in the references at the end of the paper.

Resilience Formalization

Following this principle, the resilience variable or index is first estimated, then entered into the multivariate model as one of the determinants of the phenomenon of interest. Alternatively, resilience determinants may be left separated and employed directly in the multivariate model. Normally the estimation framework uses dynamic panel data,[5] and at least two rounds of data are needed.

Analytically, a very general model can be represented as follows:

$$Y_{h,t} = f\,(R_{h,t-1}, X_{h,t-1}, Z_h \ldots, S_{h,t-1}) \qquad (3)$$

Where the outcome of interest *Y* for the household *h* is measured at time *t.* This is a function of the resilience capacity of household *h* at time *t-1* (measured beforehand, i.e. with the previous data round); a vector *X* of time-variant socio-economic characteristics for household *h*; a vector *Z* of time-invariant characteristics for household *h*; and a vector of shocks *(S)* measured at time *t*. Note that the vector of shocks can be either idiosyncratic or covariant.

Two potential sources of bias can arise while estimating resilience as an explanatory variable: a) the endogeneity of the resilience index to the outcome of interest and b) potential multicollinearity among the explanatory variables included in the regression model.

Multicollinearity exists when the no-covariance assumption is violated, i.e. when there is some covariance between two (or more) variables within the model.

$$Cov\,(X_1, X_2) \neq 0 \qquad (3)$$

In cases of significant collinearity, least squares estimates will produce large standard errors. One way to control for this is through a preliminary correlation analysis or by examining the factors that affect the ability to draw reliable inferences.

The second potential source of bias is endogeneity, which arises when the resilience index is jointly determined with the outcome of interest, or is correlated with the error term. Therefore the assumption of no covariance between one of the variables of the model and the error term is violated:

$$Cov\,(X_i, \epsilon_i) \neq 0 \qquad (4)$$

In (4) one of the regressors is correlated with the error term of the estimated model. The presence of endogeneity will bias the estimation of the parameters of interest. There are different ways to deal with endogeneity depending on its source (omitted variable bias, reverse causality or measurement error). Potential solutions include analysing correlated missing regressors or using instrumental variable approaches.

5. Pseudo- or synthetic panel data may work as well.

Resilience as a Non-Linear Relationship

Most variables that can be used in a resilience estimation model have (both spatially and temporally) non-linear or quadratic effects on it. This means that the relationship between variables changes at different magnitudes. The existence of non-linear relationships as part of resilience has been broadly accepted and/or suggested in fields including ecology (Gunderson and Holling 2002), geography (Hassink 2010) and, more recently, development (e.g. Barrett and Constas 2014). If resilience measurement includes the possibility of non-linearity, we need examples of how to proceed analytically.

The most typical example in social science is Ganzach's (1997) model of children's educational expectations. In a linear model, the educational level of both parents should be high in order to predict high educational expectations for the child. In a non-linear model with an interaction term and quadratic forms, it is possible to assume that only one parent's educational level needs to be high for the child's expectation to be high.

An example related to resilience is education. Education is highly non-linear on resilience in that its short-term effects are very small (in fact, education can even be negative for resilience capacity, reducing money availability and human resources). Yet long term, education is very positive: it typically contributes significantly to household resilience in panel-data analysis (see d'Errico and Pietrelli 2015). To the best of our knowledge, no clear and sound evidence exists about quadratic effects on resilience. However, income diversification could have quadratic effects on resilience capacity: diversifying income sources is positive for dealing with shocks; however, too many income sources can reduce the expected return from each of them and their profitability.

Non-linear effects can be mis-specified if estimated with linear regressions (Brandt, Kelava and Klein 2009; Bohrnstedt and Marwell 1978; MacCallum and Mar 1995). SEMs overcome this problem (Marsh et al. 2004, Schumacker and Marcoulides 1978) but they have been little used (Brandt, Kelava and Klein 2009). Kenny and Judd (1984) were the first to develop an approach for estimating non-linear SEMs. Marsh et al. (2004) relaxed almost all the constraints presented in Kenny and Judd (1984). Brandt, Kelava and Klein extend this approach by presenting one model that includes both interaction and quadratic effects.

Following Kelava and Brandt (2009), one possible application to resilience would be the following:

$$Res = \alpha+\gamma_1\,\xi_1 + \gamma_2\,\xi_2 + \omega_{12}\,\xi_1\,\xi_2+\omega_{11}\,\xi_1^2+\omega_{22}\,\xi_2^2+\zeta \qquad (5)$$

Klein and Muthén (2007) reduce the computational complexity and number of interaction limitations by introducing a quasi-Maximum Likelihood estimation model for SEMs with quadratic forms. Song and Lee (2004) propose a Bayesian analysis of SEMs with non-linear covariates. Wall and Amemiya (2007) adopt a flexible mixture model and a pseudo likelihood approach. Another very interesting study is that of Lee et al. (2004) where different methods for non-linear structural equations are presented.

Besides the technicalities of the estimation procedure, it is quite complicated to find out what type of non-linearity is required: quadratic forms, cubic forms and interaction terms all need to be evaluated and supported by data before they can be confirmed. Only once the economic model is carefully designed and supported by evidence will it be possible to move to the econometric estimation of non-linear relationships in resilience analysis.

Resilience as a Hierarchical Context-Dependent Relationship

A factor that is often overlooked in the dynamic analysis of resilience is that households are often sampled from the same communities or villages. If there is a correlation within communities in terms of their resilience levels, parametric regression analyses may become unreliable unless the community effects are explicitly controlled for. If there is clustering (e.g. at community level), it would be appropriate to fit a hierarchical or multilevel model.

The rationale for using multilevel models to analyse hierarchical data is well developed and broadly accepted (Skrondal and Rabe-Hesketh 2004, Di Prete and Forristal 1994, Hox 1995). When units are clustered, classical regression analysis is not suitable because the underlying hypothesis of the independence of the observations is violated. For instance, perhaps the analyst wants to understand which household and community characteristics influence the probability of transitioning from being non-resilient to being resilient. In this case, households in the same communities will probably be more similar to each other than households in different communities: the exposure to covariate shocks is likely to be the same for households in the same communities, as are their underlying livelihoods systems and their resilience capacity to covariate shocks. As a result of this dependency, standard errors could be estimated with a downward bias, so inferences about the effects of the covariates will be incorrect, generating false significant results (Hox 1995).

A simple solution would be to use robust methods (i.e., capable of yielding similar results from different distributions or populations) to estimate standard errors. However, when the multilevel structure is an important dimension in the analysis, multilevel models are more appropriate as they exploit the hierarchical data structure. In such instances, the effect of accuracy within a context or for a given distribution is more important than consistency across contexts.

Analytically, and for illustration, the following three-level linear model can be specified where the first level is *time* (t=0,1), the second is the *household*, (j=1...c) and the third is the *community* (k=1....n). c is the number of households in the community. The outcome variable is the unobserved continuous variable – or the latent variable – Y*, the resilience capacity at time t.

$$Y^*_{tjk} = \beta_0 + \sum_{s=1}^{n} \beta_s X_{stjk} + \sum_{m=1}^{n} \beta_m C_{mtjk} + u_{tjk} + v_{jk} + z_k \tag{6}$$

Note that in this specification X is a vector of s household-level variables and C is a vector of m community-level variables. The random error can be decomposed into three uncorrelated components: u_{tjk} is the idiosyncratic error term, v_{jk} the household-level random error, and z_k the community-level random error.

Therefore equation (x) represents a multilevel longitudinal model where the temporal dependency across units is factored in, as well as the dependency between the units and the community to which they belong.

With at least two time periods, equation (x) can be differenced out to construct a difference in difference model where unobserved time invariant heterogeneity can be purged out (the error term u). The model thus becomes:

$$\Delta Y^*_{jk} = \sum_{s=1}^{n} \beta_s \, \Delta X_{sjk} + \sum_{m=1}^{n} \beta_m \, C_{mjk} + \varepsilon_{jk} + \pi_k \qquad (7)$$

Where Δ indicates the first difference operator, and the error terms are expressed as ε is equal to $\Delta\ v$ and π is equal to $\Delta\ z$.

In this illustrative example, a binary indicator – R – could also be constructed where the resilience status is a dichotomous variable. Specifically:

$$R_{jk} = \begin{cases} 1 = \text{Household } jk \text{ becomes resilient if } \Delta Y^*_{jk} > 0 \\ 0 = \text{Household } jk \text{ remains non-resilient if otherwise)} \end{cases} \qquad (8)$$

In this analytical framework, the probability of becoming resilient can be modelled with a binary model (i.e. a probit specification) where the latent variable ΔY^*_{jk} is modeled following equation *x1*. Therefore the final specification (*x1-x2*) could be represented with a two-level probit model, where the first level is the *household* and the second level is the *community*.

In this model, by taking first differences, a more robust model is obtained than in equation *x*, where covariates can be correlated with *u* while they are assumed to be uncorrelated with *v* and *z*. However, the real added value lies in the fact that the multilevel structure facilitates the control for unobserved community-level heterogeneity, an important dimension that could influence the probability of becoming resilient.

V. Data Requirements for Measurement

Household resilience estimation models can be estimated in a static or a dynamic framework using household surveys with a large number of variables that describe the resilience dimensions and the outcomes of interest. Ideally, nationally representative datasets[6] should be used. The basic difference between static or dynamic frameworks is that the former refer to the availability of cross-sectional data and the latter imply a time dimension, and therefore require the availability of longitudinal or panel data. A static framework can only give a snapshot of reality and is therefore inherently descriptive.

6. Surveys such as the Living Standards Measurement Surveys would be required. These include questions on income, income-generating activities, access to basic services, social networks, formal and informal safety nets, productive and non-productive assets, living conditions, and health and educational services.

A dynamic framework may include time-varying dimensions or covariates, or changes in the outcome variable of interest. In the multivariate regression framework where resilience is indexed to an outcome (section 4) or when resilience is modelled as an outcome (section 3), one could model the effects of changes in the resilience construct on changes in the outcome, or vice versa (changes in the determinants or explanatory variables on changes in the resilience outcome), therefore taking into account inter-temporal dynamics in the variables of interest.

Panel datasets are particularly suitable for conducting the most complete quantitative analysis of resilience dynamics. Alternatively, pseudo-panels could be constructed provided that a number of econometric properties hold (see Dang and Lanjouw 2013 for an exhaustive treatment of this topic). Given the systemic nature of the resilience construct, household-level datasets should be complemented by other data 'layers', e.g. community or ecosystem data. Although optimal, a multilevel treatment of resilience measurement is beyond the scope of this quantitative brief.

VI. Summary and Conclusions

This briefing seeks to provide guidance on how to carry out quantitative analysis for resilience measurement. The analytical aims of resilience measurement have been presented as two frameworks: the first focusing on the procedures used to construct resilience variables, and the second addressing the procedures used to examine relationships in which resilience may be a predictor variable. The importance of defining resilience clearly was emphasized.

To develop these ideas, resilience was considered as a multidimensional variable described as a function of a number of dimensions that express different aspects of resilience. Unlike temperature or rainfall, resilience does not have direct physical indicators or a straightforward corresponding count. Like many things measured in development, it cannot be directly observed and measured. However, resilience can be represented as clusters of indicators and each one can be examined separately. If the dimensions of resilience are aggregated into a unique index, factor analysis and structural equation models are the recommended approaches. If resilience is employed as a regressor in a well-being model, then endogeneity and multicollinearity problems should be addressed. To address nonlinear relations between resilience and its determinants or context-specific relationships, more sophisticated econometrics exist, but these are more computationally complex and not easily implementable in the field. Over the past few years, some studies have been carried out that reflect the guidance in this briefing while also employing a wider set of analytic techniques. Examples include the FAO exercise in Somalia[7] and in Senegal and Mauritania;[8] and TANGO studies related to the evaluation of PRIME in Ethiopia.[9]

7. See www.resilienceinsomalia.org
8. Reports forthcoming.
9. See http://www.fsnnetwork.org/measuring-resilience-ethiopia

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FSIN was launched in October 2012 under the leadership of FAO, IFPRI and WFP to help build sustainable food and nutrition security information systems. One major objective is to provide access to standards, methods and tools on food and nutrition security (FNS) information systems.

Resilience has recently garnered intense, wide spread interest among FNS practitioners and policy makers because it focuses attention on people's and communities' capacities to reduce their exposure and cope with and/or adapt to shocks and stressors. However, a common understanding of how to identify and measure the factors that predict various dimensions of well-being, such as food security, in the face of shock and stressors is lacking. The ability to evaluate the impact of resilience programmes and the opportunity to track progress depend on effective measurement and clear understanding of plausible cause-effect relationships related to resilience. In this context, the *Resilience Measurement Technical Working Group* (RM-TWG) was established by FSIN to identify and promote means of operationalizing the concept of resilience in humanitarian and development practice.

Operationalizing resilience as a focus of measurement requires the provision of credible, data-based insights into the attributes, capacities and processes observed at various scales (e.g., individual, household, community and national). Therefore, the RM-TWG promotes the adoption of best practice in resilience measurement through collaborative development of three primary outputs published as a Technical Series:

- A report that provides a definition of resilience along with resilience measurement principles;
- A report that provides a common analytical model and causal framework for resilience measurement; and
- A set of technical briefings that provide guidance on specific aspects of resilience measurement.

These outputs provide practical guidance for those working in field settings and serve as a reference for continued discussions on how to collect measurement data on resilience that is accurate and useful.

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